Modelling Urban Growth: Towards an Agent Based Microeconomic Approach to Urban Dynamics and Spatial Policy Simulation

Donghan Kim

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Centre for Advanced Spatial Analysis
Bartlett School of Planning
Bartlett Faculty of Built Environment
University College London
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Declaration

I, Donghan Kim, confirm that the work presented in this thesis ‘Modelling Urban Growth: Towards an Agent Based Microeconomic Approach to Urban Dynamics and Spatial Policy Simulation’ is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

Urban growth, urban sprawl if uncoordinated and dispersed, can be considered one of the most important policy agendas in modern urban regions. While no single policy option or remedy exists, understanding the urban growth system is the first step towards sustainable urban growth futures. Spatially explicit and dynamic urban growth models provide valuable simulations that encapsulate essential knowledge in planning and policy making such as how and where urban growth can occur and what the driving forces of such changes are.

Over the past two decades, cellular automata (CA) models have proven to be an effective modelling approach to the study of complex urban growth systems. More recently Agent Based Modelling (ABM) has developed to yield a useful framework for understanding complex urban systems and this provides an arena for exploring the possible outcome states of various policy actions. Yet most research efforts of this sort adopt physical and heuristic approaches which tend to neglect socio-economic dynamics which is critical in shaping urban form and its transformation.

This thesis aims to develop an agent based urban simulation model which has a more rigid theoretical explanation of agent behaviour than most such models hitherto. However, before developing such an agent based model, this study first conducted a series of experimental simulations with two well-known generic CA based urban models, SLEUTH and Metronamica, in order to better understand the complexity of designing and applying this class of urban models. Although CA and ABM are two distinctive modelling approaches, they share certain fundamentals concerning the complexity of systems and thus the empirical simulations with widely used CA models provide useful insights for the development of a new dedicated agent based urban growth model. For this purpose, each CA model is calibrated to the study area of the Seoul Metropolitan Area, Korea. The research then moves towards developing an agent based model based on microeconomic foundations. Utility maximising residential location choices made by households are modelled as the main impetus for urban growth through agglomeration and sprawl. Furthermore, based on such urban dynamics, alternative planning policy options such as greenbelts and public transportation are simulated so that their impacts can be clarified and assessed. In this way, the model is also able to examine how planning policies alter the economic utility of households and redirect market-led urban development. These results confirm the unique value of such modelling approaches. Yet, new research challenges such as the estimation of model parameters and the use of such models in planning support continue to dominate this field and in conclusion, we identify future research directions which build on these challenges.

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Chapter 1: Introduction

1.1. Background and Goals

Urban growth, which is considered as sprawl if uncoordinated and undesired, is one of the most prominent concerns in modern cities and planning policies. Such sprawling urban growth is a more dominant form of urban development pattern these days and is generally considered undesirable due to negative effects such as the loss of open space and damage to natural environment. Contemporary planning agendas like “sustainable development”, “smart growth” and the “compact city” are all explicit or implicit reactions to dispersed and excessive urban expansion. Yet, there is no one single remedy or policy measure to manage urban growth. While coping with urban growth involves various socio-economic policy measures, understanding the complex urban growth system is the first step towards making sustainable urban forms.

Planning as a future oriented activity leans on scientific knowledge about urban systems, and urban models have been playing an important role in supporting planning policy. However, the style of urban models has changed over time, reflecting the evolving view of urban systems as well as trends in planning policy and practice. In the past, the urban system has been typically studied in a top-down and aggregate manner, and the predictive and operational urban models in this regard have been developed to support planning policy and practice. In terms of practical planning support, the early generation of urban models which appeared in 1950’s usually had a tight link to the actual planning process with a well-defined problem solving role. On the other hand, now the urban system is increasingly conceived as a complex system which is a construct of non-linear interaction between diverse members and elements of the system. Scientific knowledge about the future is nevertheless crucial in planning and urban modelling, but recent urban models focus on disaggregate and dynamic approaches with a less operational and predictive manner. With regard to planning support, recent urban models tend to provide a more general knowledge framework for the wider set of participants and the general public although some urban models and planning support systems still aim to solve particular urban problems based on such a policy analysis perspective. No one modelling approach replaces the need for the others. However, it is important to note that disaggregate and dynamic urban modelling approaches suggest a new way to understand urban systems and hence to support planning policy.

In this context, there has been a growing interest in cellular automata systems and agent based urban models since the late 1980's. These models are dynamic and disaggregate and offer an innovative way to study urban systems as a self-organising system. These models have not only provided effective frameworks to study complex urban systems but also helped to test the effect of planning policy options under the various "what if?" assumptions and as computational simulation models. Some cellular automata models are developed into generic modelling packages which are ready to be used for various urban regions, and the value and strength of such cellular automata models have been well proven in a range of practical applications over the past two decades. However, these types of urban models usually aim to maximise behavioural realism with a focus on physical aspects of urban systems and typically rely on ad-hoc model development to achieve such modelling goals. As a result, these models have limitations in explaining the socio-economic dimension of urban systems.

This research defines an urban system as a complex system which is mainly characterised by bottom-up and self-organising development processes. We believe that cellular automata and agent based simulation models are among the most effective approaches to capture such urban systems among different modelling approaches to urban growth. However, this research also considers that the introduction of traditional socio-economic models and theories to the cellular automata and/or agent based modelling framework can provide us with a new opportunity to study complex urban systems. In this case, urban growth simulation models not only help us to understand self-organising complex urban growth process in a spatio-temporal framework but also enable us to capture the key socio-economic drivers of such urban growth processes.

To better achieve an empirical understanding of the development and use of complex urban models, this thesis firstly conducts two experimental simulations with widely used generic cellular automata models: the SLEUTH and Metronamica models. Although cellular automata and agent based models are distinctive approaches to urban systems, they share a common background in complex theory which can be best understood through disaggregate and dynamic modelling approaches. Thus full scale empirical application of such generic cellular automata urban models can provide useful insights for the development and use of intended agent based models. To this end, this thesis calibrates SLEUTH and Metronamica for the Seoul Metropolitan Area, South Korea (hereafter Korea). It also designs practical planning scenarios to explore the functionality of the models on the one hand and to draw practical planning implications for the study area on the other hand.

After the simulations with SLEUTH and Metronamica, then the thesis develops an agent based urban growth simulation model based on urban economic bid-rent theory. The benefit of urban growth simulation particularly with agent based modelling includes an understanding of how the interactions between individual agents such as households result in a system change at the whole urban scale and how such spontaneous actions are further affected by possible planning policy options. While most complex science based urban models focus on realistic representations of the urban system without theoretical explanation of underlying driving forces of the urban process, this research aims to develop an agent based model with a stronger theoretical explanation on agent behaviour and urban formation. To this end, microeconomic residential location choice theory is adopted in the agent based model. The theoretical models are firstly built and implemented in a Euclidean grid space $\Re^2$ with varying economic, spatial, and policy conditions. Then theoretical models are further applied to the case study area of the Seoul Metropolitan Area in order to examine the model behaviour for empirical applications.

1.2. Research Scope and Methodology

This thesis carries out three distinctive simulations: calibration of SLEUTH, calibration of Metronamica, and the development of an agent based model. Implementing and developing such related but unique urban models requires a multidisciplinary research approach. Thus this research is structured around a series of different methods and techniques. These include a review of the urban planning and modelling literature, a preliminary GIS based spatial analysis to examine the characteristics of the study area as well as the outcomes of simulation models, the calibration of SLEUTH and Metronamica which in turn have unique dedicated methods, microeconomic theoretical modelling to define agent behaviour, and Java programming to develop the intended agent based model.

The thesis starts with a literature review concerning the general trends in urban planning and urban modelling. This is to understand the overall nature of urban models and their use for planning. Then it reviews the notions and applications of cellular automata and agent based models. This provides the necessary foundation knowledge for the calibration of SLEUTH and Metronamica and enables us to develop the proposed agent based model.

Understanding the nature of the study area and planning problem is also crucial to the calibration of the generic models and the development of a dedicated model. Such examination of the case study area is necessarily based on a mixed use of qualitative and quantitative approaches. The descriptive analysis of the study area is partly based on the qualitative evaluation of the area but more importantly it is based on quantitative methods such as statistical figures and GIS based mapping and data processing. This provides a spatial as well as policy context for all simulation works.

The calibration of SLEUTH and Metromamica from a technical perspective is a process to determine the best fit model parameters but fundamentally it is a way to adapt the behaviour of these generic models to a given study area. The calibration of dynamic cellular automata models is typically achieved by analysing historic spatial data for the study area; however, the specific calibration method differs by the model since each model has a unique structure and model parameters. The calibration of SLEUTH relies on a quantitative method which involves a comparison of statistical metrics automatically generated by the model. On the other hand, the calibration of Metronamica takes the form of a qualitative approach which involves intensive visual map comparisons. The calibration of the SLEUTH and Metronamica models has been conducted with such methods respectively. Details of the calibration processes and results are covered in the relevant chapters.

Contrary to the cellular automata model, agent based models more clearly define decision making entities and their behaviour that evoke the system change. Although the strength of the agent based model includes the possibility of developing the model with simple ad-hoc decision making rules, this thesis reviews and adopts microeconomic residential location choice theory as a key logic of the agent based urban growth model. Then such microeconomic models are embedded in the agent based modelling framework through a computer programming development. Agent based modelling is indeed a general modelling approach which can be used across a wide variety of disciplines and domains, but the development of an agent based model can be generally achieved by dedicated computer programming. To facilitate the development of the agent based model, many agent based modelling toolkits have been developed. Yet, what such toolkits essentially do is to provide an environment that facilitates computer programming. Typically object oriented programming languages such as Java and Objective C are used to develop the agent based models. This thesis used the Java programming language in a non-proprietary agent based modelling toolkit Repast Simphony.

All the above models are applied to a single case study area, the Seoul Metropolitan Area, which is the capital region of Korea. All necessary spatial data for the preliminary GIS analysis and simulations are obtained from public sector sources in Korea. While the use of custom data can improve the result of simulations, this research attempts to use publicly available data to minimise data building efforts and to conduct urban modelling under conditions of limited data availability. Since each model used and developed in this thesis has different data requirements, specific layers, spatial resolution, temporal dimension, and area coverage vary by each simulation. Details of the data requirements and the inputs used are described along with each simulation.

Finally, this thesis synthesises the implications from the theoretical reviews and the findings from the experimental case studies to draw broad implications for the development and use of complex urban models. Although a comparison of different models is not the main focus of this research, the simulations with three different models for the same study area provide a valuable opportunity to better understand complex urban models and their uses. Discussions in this context are provided in the concluding chapter.

1.3. Thesis Outline

This thesis has three main parts. Part one deals with contextual materials for this research. It reviews trends in urban planning and urban modelling and then examines the methodology of cellular automata and agent based models. Part two presents the core empirical works of this thesis. It includes three distinctive but related simulation works: simulations with the generic model SELUTH and Metronamica respectively and a simulation with the agent based model developed for this research. Part three concludes the thesis. It discusses implications and limitations of this research. Details of each chapter are as follows.

Chapter 1 introduces the thesis. It firstly describes the background and goals of the research. Then it also presents the research scope and methodology.

Chapter 2 reviews the changes in planning thinking and urban modelling styles. Although urban modelling is an independent research domain, its history and development has a close relationship with planning thinking and practice. Styles of both planning and urban modelling have changed over the time, and this chapter investigates the relevance of the recent urban modelling practices in the contemporary planning context.

Chapter 3 provides an overview of cellular automata and agent based models in general as well as in urban modelling. It explores general principles of cellular automata and agent based models as well as tools to build such models. Then it reviews cellular automata and agent based models for urban modelling and discusses their potentials for studying urban systems.

Chapter 4 describes the study area of the urban growth simulations, the Seoul Metropolitan area, Korea. This thesis attempts to calibrate two generic cellular automata models and develops one prototype agent based model for a single case study area. To calibrate and/or develop an urban model, it is necessary to understand the nature of the study area beforehand. To this end, a descriptive analysis is provided in this chapter. This includes a brief historical background of the area, its geographic and topographic characteristics, trends in population growth, and processes of past and recent urban development. All together, this chapter provides the spatial and planning context for the urban growth simulations in the next chapters.

Chapter 5 presents the calibration of the SLEUTH model. It firstly describes the key characteristics of the model in terms of data requirements, model structure and behaviour, and the calibration method. Then it moves towards the actual calibration of SLEUTH for the Seoul

Metropolitan Area. The essential parts of the model calibration process, i.e. determination of the best fit parameter, as well as the final results, are explained. Then, with the chosen parameters at hand, simulations for the future are conducted with regard to two future growth scenarios such as business as usual and deregulation of the greenbelt. However, although the SLEUTH model has a proven capacity for practical application for diverse urban regions, future simulation in this research is limited by inadequate input data. The results and implications are discussed at the end of the chapter in this context.

Chapter 6 carries out the calibration of Metronamica. The chapter structure is the same as that of chapter 5. It starts with the description of the model and then illustrates the detailed calibration process as well as the results of model calibration. However, in terms of future simulation, this chapter has richer content. Three alternative scenarios, notably business as usual, deregulation of the greenbelt, and the introduction of high-speed rail, are designed to study alternative futures for the study area. The chapter concludes with implications of these simulations for planning support as well as complex in urban modelling.

Chapter 7 presents the key modelling effort of this thesis – an agent based urban growth simulation model based on a microeconomic approach. It firstly introduces the tradition of urban economics and explains underlying theoretical assumptions appearing in the typical urban economic models. To develop the microeconomic agent based urban growth model, it defines the bid-rent models to explain the residential location choice of agents. These microeconomic models are adopted and extended from the classic bid-rent approaches. Then the chapter shows several theoretical simulations with varying spatial conditions. After these simulations, the abstract models are then applied to the case study area. The simulation results are presented with some planning scenarios which confirm the value of this modelling approach. New possibilities and limitations of this approach are discussed in the concluding part.

Chapter 8 concludes the thesis with a discussion of the implications and limitations of the research. It firstly covers the limitations and future development of the proposed agent based model. Although this thesis proposes an innovative way of studying urban systems by integrating two heterogeneous methods, i.e., urban economics and agent based models, the proposed model has limitations in practical urban modelling. Further work on the empirical estimation of model parameters as well as time matching is necessary to develop this model for further practical use. Future work in this regard is discussed. In addition, from the combined experiences with the calibration of SLEUTH and Metronamica and the development of the agent based model, this chapter discusses broader implications for complex modelling and planning support.

Chapter 2: Trends in Urban Planning and Urban Modelling

2.1. Changes in Planning Thinking

Planning is a means for making better urban spaces and quality of life, but the meaning and scope of planning has changed over the time reflecting broader socio-economic perceptions about urban systems. It is hard to pinpoint a single origin of urban planning, but modern urban planning started as a field to improve poor physical conditions in industrial cities in the 18th and 19^{th} centuries. Although the main focus of planning still includes measures to improve the physical aspects of cities, the planning domain has eventually expanded to embrace various socio-economic and political aspects of urban space. In this process, planning has been shaped by a wide variety of intellectual traditions (Friedmann, 1987), and the major focus of planning also varies by specific spatial context unique in each space. Thus, defining planning is not a trivial task.

Regardless of the complex nature of planning, it is worth taking a look at the theoretical development of/in planning to better understand the ontology and epistemology of planning. Friedmann (2003) provides a useful framework to understand the nature of planning and distinguishes *theories in planning* and *theories of planning* to this end. Firstly, *theories in planning* reside in various specialisation areas of planning activities such as land use, transportation, urban design, and so on. These theories are not about planning itself but rather about many different sub fields in planning. On the other hand, *theories of planning* deal with the fundamental nature of planning activities, and they consider planning as a decision making process to attain certain types of human rationality such as instrumental and communicative rationality.

Controversial yet crucial to the understanding of the common characteristics of planning activities and policy making are *theories of planning*. These *theories of planning* cannot provide substantive knowledge to cope with substantive planning agendas and tasks, but they define and explain what planning activity is all about and how it should operate. In other words, these theories define the norms and scope of planning. Largely affected by public policy science and other social theories, there have been several distinctive approaches to planning such as comprehensive, advocative, incremental, and communicative planning. Although all of the above styles together have shaped contemporary planning, two major influences are rational comprehensive and communicative planning paradigms. These two planning theories define the nature of planning from different perspectives, but it is important to understand the nature and characteristics of the two planning approaches because these theories provide different contexts for urban modelling.

In the past, planning thinking was largely dominated by the rational comprehensive planning model which in turn has its intellectual tradition in the logical positivist policy analysis tradition. Logical positivists argue that fact can be separated from value and that only objective facts derived from scientific methods can be accepted as decision making criteria. In this case, subjective and value-laden knowledge are rejected for decision making. In this thinking, planning is seen as a course of well-defined actions to achieve instrumental rationality for a given policy goal. The following describe some of the key notions of comprehensive rational planning.

- Planning is seen as a problem solving action.
- Planning is a process of finding and implementing the best or satisficing[1] solution to the problem.

[1] A decision based on bounded rationality. Rational decision making in this context is confined by limited information and resources and concludes with a satisficing solution rather than best

- Planning is a scientific and value-free process without public involvement.
- Planners identify and address common public interests.
- Planners are seen as policy analysts who generate value-free scientific knowledge and evaluate alternatives, and top decision makers make a choice based on such information and knowledge.

Regardless of some conceptual variations, planning in this case is basically described as a linear process which includes the identification of policy problems and available resources, the generation of potential alternatives to attain the policy goals, and the determination of best solutions, and the implementation of chosen measures. A conventional view of such a rational planning process is depicted in Figure 2.1.

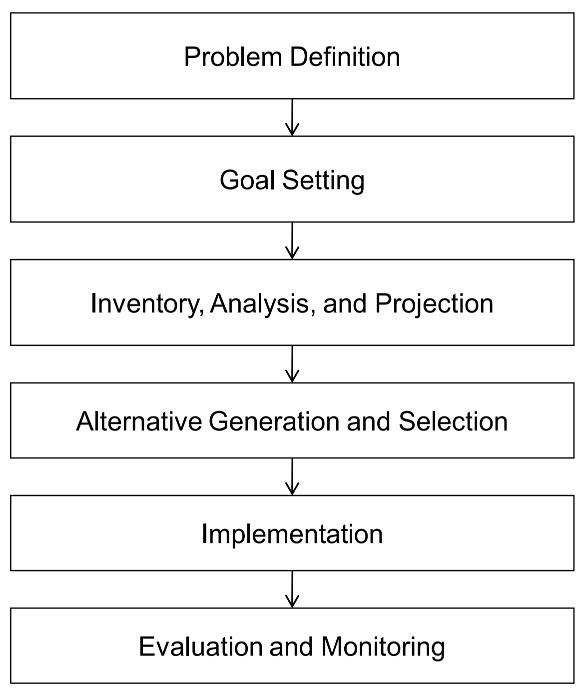

Figure 2.1. A Typical View of the Comprehensive Rational Planning Process

one. The term and notion was proposed by Herbert Simon (1957).

However, there have been some critiques of the key notions that support rational comprehensive planning. This is also a large topic and can be examined from various angles, but some examples are as follows. For instance, the key positivist notion of value-free objectivity has been largely questioned by new styles of social thinking and theories such as the Habermasian theory of communicative actions. The theory of communicative rationality emphasises the role of communication relative to that of scientific fact in human rationality. It has been argued that the separation of fact from value is not always possible in the study of social systems. Another example includes the development of public choice theory. Public choice theory explained government failure and pointed out that government officials and politicians are affected by their self-interest in public policy making. In this view, planners and decision makers can be also biased and self-interested people, and they have limitations on representing common public interests.

Planning has embraced these types of new social thinking, and planning as a comprehensive rational decision making process in the light of instrumental rationality has been challenged for a couple of decades. At the same time, as social interest in democratic pluralism grows, the idea of planning without public involvement has become less acceptable in many democratic societies. In this context, communicative planning (Forester, 1989) or collaborative planning (Healey, 1997) has become a dominant planning style since the 1990's. This type of planning thinking emphasises the involvement of diverse stakeholders and participants and consensus building through argument and coordination among various players in the planning process. Healey (1992) summarised the key concepts of communicative planning as follows:

- Planning is defined as an interactive and interpretative process. Formal techniques and analyses are one form of discourse among many.

- Interaction in the planning process engages individuals with others through their own meaning systems, and communicative action thus focuses on reaching achievable levels of mutual understanding.
- Those interactions are based on respectful discussion within and between participants.
- Planning not only involves generating a set of policy measures but also creates arenas for public discussion where those measures are formulated.
- Diverse forms of knowing, understanding, appreciating, experiencing, and judging can play a role in the planning process. Nothing is disregarded unless it is outside the planning agenda.
- A reflective and critical capacity is built through the communicative process.
- These inbuilt interactions promote democratic pluralism.
- Interactions and communications are not just about bargaining over conflicting interests but more importantly about gaining mutual learning and understanding among participants.
- The communicative process has potential to transform material conditions by reaching agreement about what should be done.
- The purpose of communicative planning is to prepare and implement planning policy in mutually agreeable ways.

In this communicative planning view, planning is considered as value-laden collective action towards shared vision through consensus building, and planning has become much more diversified and fragmented in its scale and context. Consequently planning now has been increasingly recognised as a complex process which consists of different rounds and sub arenas with diverse actors. Thus planning is rather conceived as a non-linear process which involves possible deadlocks and breakthroughs in any of these rounds and arenas (Gils and Klijn, 2007). Such a planning process is depicted in Figure 2.2.

Adapted from (Gils and Klijn, 2007)

Figure 2.2. An Example of a Complex Planning Decision Making Process

Table 2.1 compares the key differences of rational planning and communicative planning. What is important here is its implication for urban modelling. Of course urban models are not simply affected by *theories of planning* but are more substantially influenced by various specialised *theories in planning*. However, an understanding of the nature of planning policy making provides a meaningful context for the role and use of urban models. For instance, while urban models traditionally have been policy analysis tools which have relatively well defined tasks for a limited number of planners and decision makers, recent urban models have less tangible links with specific planning tasks and tend to offer more general knowledge on urban systems for a wider range of players. The next section further reviews the characteristics and supportive roles of urban models.

Table 2.1. Comparison of Rational and Communicative Planning

	Rational Planning	Communicative Planning
Philosophical Background	Positivism	Critical theory
Perception of Human Rationality	Instrumental rationality	Communicative rationality
View on Knowledge	Fact-value dichotomy	Value-laden
Planning Process	Linear process	Complex non-linear process
Means of Making Decisions	Best(or satisficing) solution through expert knowledge	Consensus building through public involvement
Role of Planner	Planner as policy analyst	Planner as facilitator

2.2. Trends in Urban Modelling

Methodological Diversification

Scientific models are simplifications of target systems under study in the real world. It is important to understand that the purpose of a model is not to replicate reality as it is but to capture what is considered as necessary or essential to represent the system. Thus no model fully contains all aspects of the reality. Complete replication of reality is not the purpose of model building, and indeed only reality itself can represent reality as it is. However, although no models give a complete picture of the system, models provide a scientific framework to understand the reality since models are typically built upon proven theoretical knowledge and analytical methods.

Urban models share the fundamental characteristics of scientific models, and they have a specialised focus on urban systems. However, the main target of urban models has not been the whole urban system itself, which is too broad or vague to model, but has been the spatial changes caused by certain socio-economic activities or by other perceived factors. Thus the term urban model does not necessarily mean an abstraction of the entire urban system in any possible way but focuses more narrowly and mainly refers to models of land use and land cover change in an urban context.

The history of such urban modelling traces back to the late 1950's and early 1960's[2]. In those times the land use transportation models were widely introduced in the planning domain to address the interrelationship between transportation and land use change. These urban models were particularly built around spatial interaction theory which has an analogy with Newton's gravity law. Since then, over the last five decades, diverse urban modelling methods as well as computer technologies, for instance econometric analysis and Geographic Information Systems technology, have been introduced in an effort to improve models of urban systems. As a result, various types of urban models are currently available for practical planning support[3].

Since such urban models can be based upon various types of data, methods, theories, and philosophies, the classification of urban models can vary in analytical purpose. Among many different types of urban models, particularly important and influential urban modelling classes to be briefly introduced in this chapter are spatial interaction models, econometric models, cell-based models, and agent based models (Iacono, Levinson, and El-Geneidy, 2008). This classification does not cover all types of urban model, but it clearly summarises major

[2] The Chicago Area Transportation Study (CATS) conducted in 1950's provided an important foundation for urban modelling and the scientific planning movement. However, more concrete forms of urban model emerged in the following decade. The Lowry model (Lowry, 1964) and its derivations are generally regarded as the first generation of urban models.

[3] For instance, the U.S. Environmental Protection Agency (EPA) has inventoried various land use change models in use. For details, see: Projecting Land-use Change: A Summary of Models for Assessing the Effects of Community Growth and Change on Land-use Patterns, 2000. EPA, Washington.

modelling approaches to urban systems and effectively presents how the focus and trend of urban models have evolved over the time. The key notions of each class are as follows.

Spatial interaction models are among the earliest class which are built around analogy with Newton's gravity law. These models are based on the notion that the interactions or movements between two locations or regions depend on their size and the distance between them. Like gravitational pull, interactions are proportional to the size and inversely proportional to distance. In this context, human movements between one location associated with particular land use types and the other location with different land use types are considered as interactions. Changes of such interactions lead to changes of land use types and vice versa. It is assumed that transportation infrastructure facilitates the interaction between locations and thus leads to changes in socio-economic activities and/or land uses.

Econometric models incorporate economic theories in the simulation of land use change. Land here is a type of economic good, and changes of land use are seen as the result of economic activities rather than that of gravitational pulls as in the previous style of spatial interaction models. The key determinants of such economic decision making behaviour relating to the land and to the dynamics of the resulting land use change vary by specific economic theories such as Alonso's(1964) bid rent theory and McFadden's(1973) random utility theory. For example, in the case of the classical bid rent theory, urban land use patterns are shaped by the land rent gradient which is fundamentally determined by the distance from the city centre (CBD) and commuting cost to the CBD. Typically it is assumed that all land users prefer to be close to the centre and that the competition is decided by willingness or ability to pay but traded for amount of transportation cost. As a result, while business and retail uses are located in the central area, residential uses are settled in the outer areas resulting in the expansion of urban boundaries.

Cell based models usually refer to cellular automata although some other types of cell based model like the Markov chain model, which focus on the transition probability of cells drawn from the statistical analysis of historic land use patterns, also can fit into this category. Unlike the cell based models solely built around statistical operations, cellular automata models focus on the autonomous interaction between individual cells along with predefined transition rules. In cellular automata systems, the main driving force of land use change is the local level interaction between cells. Such cellular models are typically built upon grid cell space, and cells have given states and other characteristics. Each cell can represent a certain type of land use that is affected by surrounding geographies. Then the states of cells are dynamically updated with a reference to the states of neighbouring cells and the cell transition rules. Such local interactions of individual cells result in overall land use change at a global scale.

Agent based urban models are among the latest methods in urban modelling. Like cellular automata models, the key notion of agent based models includes the global land use change resulting from local level interactions. However, agent based models focus on individual decision makers' behaviours and their interactions with each other and/or urban space. In order to model land use change systems, these models are often run on the cell space in order to model the changes of land use in a lattice space. Here, agents can represent various individuals or social groups who act over the cell space, and their decision making behaviour results in changes in the space, i.e. land use changes. The key to this approach is the behaviour of agents and their relationship with urban space, but agent based modelling itself does not hold an answer to this. It varies by individual application of the agent based model.

In addition to classification based on the theories and methods adopted in urban models, another classification based on their representation of space and time provides a useful snapshot for understanding the history and trend of urban models. To this end, urban models can be further categorised into spatially aggregate and disaggregate and/or temporally static and dynamic modelling styles. Aggregate models may consider characteristics of individual members in the system but describe system behaviour at a collective or coarse spatial resolution. Contrary to this, disaggregate models capture the changes in individual elements of systems with finer spatial resolution. Static models are framed at a certain fixed time point while dynamic models trace the changes in the system over a designated time period.

Since the first generation of urban models was developed in the form of Land Use Transport Interaction (LUTI) models in the 1950's and 1960's, the dominant style of such models has evolved from an early focus on aggregate and comparative static, cross-sectional approaches to more detailed disaggregate and temporally dynamic procedures (Batty, 2009; Iacono et al., 2008). This is partly due to developments in gathering bigger, more individualised data sets, as well as through dramatic advances in computation but this is all predicated on the fact that there is now general agreement that cities need to be simulated from the bottom up rather than top down. Evolution and change is central to the way cities evolve and it is now widely regarded that such dynamics must be built into the structure of the most applicable models. Whereas traditional aggregate models deal with the target system in a top down manner, recent micro urban models tend to take a bottom up perspective. In addition, while traditional urban models pay more attention to the static impact of transportation on land use change, recent urban models have focused on the dynamic transformation of urban morphology with much less emphasis on transportation *per se* and this has spurred the development of such models (Batty, 2004). Such different styles of urban model have their own advantages and limitations, and all are currently presented in the planning field. However, disaggregate and dynamic urban models are gaining in popularity in recent times.

Integration with Information Systems Technology

Computer technologies appended to urban models enhance the usability of urban models. Information technologies such as database and visualisation techniques provide necessary bridges to use urban models for practical planning support purposes. Indeed, the integration of urban models and information technology is essential to varying degrees. Since urban models are typically implemented in a computer environment, the advancement of general computer technologies has also played an important role in the urban modelling field. Planning Support Systems have emerged at such a point. While urban models tend to form the core of many Planning Support Systems, Planning Support Systems as an integration of urban models and relevant technologies enlarges the function of urban models and even transforms their value.

The term Planning Support Systems (PSS) was first coined in the late 1980's by Harris (1989). Planning Support Systems were originally regarded as information systems with the capability of employing locational models and of supporting non-routine decision making activities (Harris and Batty, 1993), but specific functionalities and underpinning theoretical frameworks vary in terms of individual software. While some are developed for particular planning projects and hence for one-off use, certain Planning Support Systems such as UrbanSim and Metronamica are designed as generic software packages and publicly available for free or in some cases at low cost.

Planning Support Systems, a type of information system[4], can be best understood from the design science perspective rather than the behavioural science approach. Planning Support

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[4] Information systems are human artefacts built around software, hardware, and related technology. There are two major research paradigms with regard to the understanding of information systems: behavioural science and design science paradigms (March and Smith, 1995). A behavioural science approach is rooted in the natural science tradition which tries to understand reality through discovery and justification. The behavioural science approach in this sense tries to discover and explain organisational and human behaviour affected by the use of information systems. Typical interests centre on the effectiveness and efficiency of organisational performance after the introduction of certain information systems. On the other

Systems have emerged and developed to support planning problem solving rather than to change the overall performance of the planning process. What distinguishes Planning Support Systems from similar sorts of information systems are their capabilities to handle spatial problems on the one hand and to serve for long-term non-routine problems on the other hand. These functions have been at the heart of the development of Planning Support Systems.

However, like the changing nature of urban planning and modelling, the focus and scope of Planning Support Systems is not standing still. As the definitions of planning can be multitudinous, there is no universal agreement on what Planning Support Systems are and what they are for. It is evolving with the advancement of computer technologies in the one hand and more importantly the changes in planning and modelling on the other hand. While the early developments focused on the designated problem solving functions of Planning Support Systems, recent advancements in computer and information technologies make Planning Support Systems much more diverse in their forms and purposes.

For instance, Harris (1989), who officially but academically coined the term Planning Support Systems, distinguished Planning Support Systems from previous computer uses in planning, although computer based urban models and Geographic Information Systems had been widely introduced in planning at that time. He highlighted the capability of employing locational and spatial interaction models as a key aspect of Planning Support Systems, as well as the capability to support non-routine decision making activities. On the other hand, Klosterman (1997) argued that the roles of information technology in planning have changed over time, reflecting paradigm shifts in planning. Then he asserted that the focus of planning has moved to

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hand, a design science approach, which is typically found in engineering, architecture, and urban planning domains, tries to create artefacts to serve certain human purposes. In this approach, information systems tend to augment human and organisational problem solving and decision making capabilities by creating new and innovative artefacts (Hevner, March, Park, and Ram, 2004).

a communicative one since the 1990's and thus that Planning Support Systems should be designed to aid achieving collective goals and common concerns. He also claimed that what distinguishes Planning Support Systems from Decision Support Systems and Spatial Decision Support Systems is the focus on long-range problems and strategic issues. Geertman and Stillwell (2003) consider Planning Support Systems as a subset of geospatial information technologies combined with necessary theories, data, information, knowledge, methods, and/or tools in order to support all or any kinds of planning task. Locational capabilities are still emphasised here, but diverse variations of Planning Support Systems in their supporting functions and contributing components are addressed. In this view, Planning Support Systems are not just specialised problem solving applications but rather broader information frameworks that embrace multiple technologies and resources useful for supporting all or parts of the planning process. Recently Batty (2008) points out the changing nature of Planning Support Systems and broadens the concept. He sees that today Planning Support Systems can take practically any information technologies to support any kind of planning activities. Their components, forms, functions, and purposes are all open questions now.

> "Planning Support Systems are not standing still. Almost all aspects of planning in its various types from urban design to regional policy have been subject to IT support and, with the fragmentation of the field, various layers of software have been exploited and built to reflect this diversity."(Batty, 2008)

The relationship between urban models and Planning Support Systems is now changing. Urban models as vehicles for scientific knowledge were once a key part of Planning Support Systems, and the latter provided an important technological framework for the former. However, the notion of planning support with urban models and/or information technologies has become much diversified. This is related to the changing role of information and knowledge in planning. We will discuss this subject in the next section.

2.3. Urban Models for Planning Support

The Roles of Information and Knowledge in Planning

Planning deals with uncertain futures, and planning policy making always requires a variety of scientific information and knowledge[5] of urban systems in various steps and tasks. The numerous activities like observing, measuring, analysing, modelling, simulating, predicting, prescribing or designing, optimising, evaluating, managing, negotiating are all subject to the consumption of information and knowledge possibly through computing support such as urban models and planning support systems (Batty, 2008).

As discussed before, planning has experienced a drastic paradigm shift from narrow physical design to a broader social science and then has expanded its scope from well-defined subject areas like housing, land-use, and transportation to all inclusive mega issues such as sustainability and democratic collaboration. Thus, the uses and roles of information and knowledge in planning policy making depend on the question of what kinds of planning style and activity we are talking about. However, the evaluation through two major planning paradigms such as rational and communicative planning hold some general answers to the role of scientific knowledge in planning.

Traditionally the use of information and knowledge in planning heavily relied on the positivist view of instrumental rationality, but views on scientific information and knowledge

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[5] It is useful to distinguish the difference between information and knowledge. While information is an organisation, analysis, and/or summary of data in a meaningful form, knowledge is an understanding based on information, experience, and study (Klosterman, 2000).

have been much more diversified after the rise of communicative or collaborative planning. In the positivist tradition, information and knowledge often took a quantified form, and only scientifically validated knowledge was accepted as a basis for decision making. "Talking with numbers" was an important virtue in the case of the rational comprehensive model of planning policy making. This tradition still continues and plays an important role in planning, but the belief and reliance on scientific and value neutral information has been significantly challenged in the modern planning process. For instance, Innes (1998) argues that several types of information play a role in communicative planning: scientific knowledge, participants' own experiences and stories, and even intuition. Participants in the communicative planning process do not really lean on technical or scientifically validated information to define the nature of the problem, to persuade others, or to decide among suggested options. Besides, the participants even reject scientific information if such information has no practical meaning or any particular relation to the policy making context. Stephenson (2000) argues that the role of technical information is not critical in the modern communicative planning process. Moreover, in a wider policy science domain, the role of policy analysis in instrumental perspective has also weakened (Heineman, Bluhm, Peterson, and Kearny, 2002). The authors argue that many empirical studies show that policy analysis based on instrumental rationality has little or no impact on actual policy making. Instead, policy analysis as enlightenment or pedagogical value has more importance in reducing uncertainty in various decision making situations.

Nevertheless, the use of scientific knowledge is always a crucial element in planning. Rydin (2007) points out that knowledge about the future is always critical in planning. Although the reality in the future could be different from the scientific prediction and the policy intents, the future state is indeed the result of planning activity and underpinning knowledge. Thus such a future would not be possible in the absence of planning and science (see Figure 2.3).

Then, Rydin further suggests seven different types of knowledge needed for the contemporary planning process: (1) knowledge of the current socio-economic and physical situation (2) knowledge of prediction of future scenarios (3) knowledge of the societal process that will lead to a future state (4) knowledge of the planning process and how it leads to the desired goals (5) knowledge of the outcome state (6) knowledge of how planning and the societal process interact to create outcome states and (7) normative knowledge of desired goals. While three are planning process-oriented value laden knowledge, the other four are empirical, descriptive, and predictive.

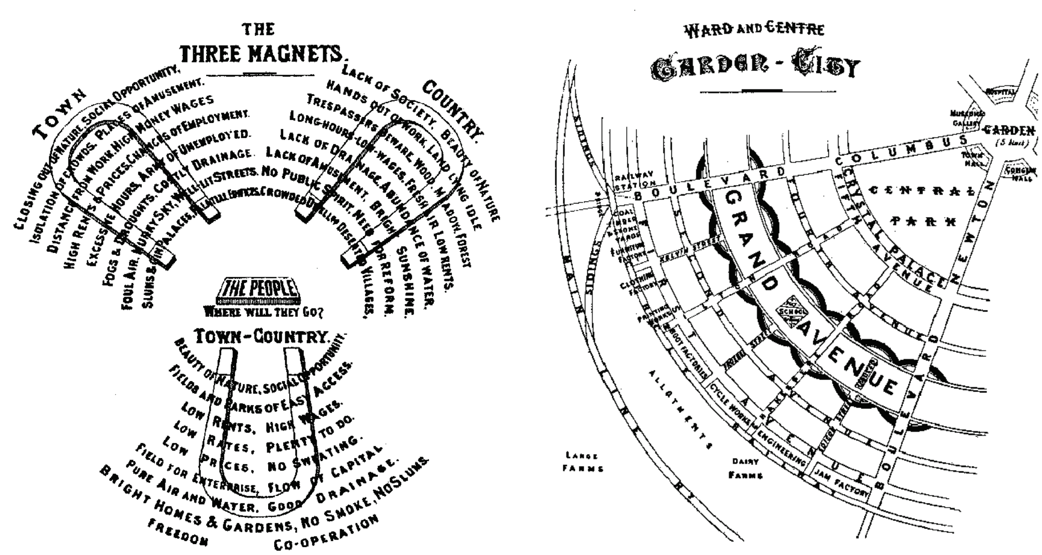
Adapted from (Rydin, 2007)

Figure 2.3. Knowledge and Planning

It is clear that scientific information and knowledge have important roles in understanding the current state and predicting future states. However, it is important to acknowledge that non-scientific value-laden knowledge is also a crucial element of planning policy making. Taking different types of knowledge into account is a complex task but a necessary task in modern planning policy making. This in turn provides valuable implications for urban models and Planning Support Systems. Instead of finding an “optimum solution” or "equilibrium state", the exploration of "what if?" questions and the provision of "story telling" discourse can be new roles for computer-aided urban models and support systems.

The Need for the Visual Representation of Urban Space

Visualisation is an important element for delivering the results of urban models for planning support. Visualisation is a universal form of human communication, regardless of whether it is for one-way dissemination or two-way exchange. Even before the era of the computer, visualisation has been an integral part of planning. Blueprints, diagrams, charts, graphs, maps were typical examples. The purpose of these visualisations is not only to aid planning by simplifying intended information but also to guide planning activity by symbolising ideas, values, and goals. Thus visualisation in planning is more than dissemination of information, and in some cases, it can hardly be replaced by verbal and textual communications. Figure 2.4 is a diagram that presents the idea of the Garden City, and it shows a classic example of the use of visualisation in planning.



Source: Ebenezer Howard, Garden Cities of To-morrow, 1902

Figure 2.4. Symbolising and Unfolding Planning Vision with Visualisation

There are different types of visualisation in a general perspective. Three visualisation styles are worth looking at in a planning support context: scientific, information, and knowledge visualisation. Scientific visualisation represents data acquired from scientific experiments and simulations to aid investigation and understanding of the data. Information visualisation aims to explore large amounts of abstract data to find hidden insights or just simply to make the stored data more accessible. Knowledge visualisation tries to improve the transfer of knowledge among people and to pursue the creation of new knowledge. While information and scientific visualisation focus on the delivery of facts, knowledge visualisation aims to further the transfer of insights, experiences, attitudes, values, expectations, perspectives, opinions, and predictions (Eppler and Burkard, 2006).

Most computer-aided urban visualisation efforts are cases of scientific and information visualisation. Urban visualisation spans from displaying outputs of urban models to creating digital representations of urban data. Langendorf (1992) argues that computer-aided urban visualisation is commonly premised on three assumptions. First, understanding any subject matter requires viewing it from diverse viewpoints with a variety of information. Second, our conception of subject matter is greatly enhanced if information is visualised. Third, visualisation facilitates communication with others. Langendorf (2000) also argues that the focus of urban visualisation has evolved from the visualisation of application data associated with planning tasks to a larger representation of urban built environment.

Urban models do not always need to be spatially explicit. Many non-spatial urban models, for instance, statistical models and systems dynamics models, have their own strengths even without the spatial visualisation of modelling results. However, for the simulation of land use change, a visual representation of model outcomes is essential to examine and present the urban land use patterns and structures.

To this end, it is necessary to link urban models with information systems technologies, especially Geographic Information Systems, and there are different approaches to this. While some models take a loosely-coupled structure, some models have built in functionality of data visualisation. The former typically stands alone as a pure model, and the latter approach usually takes a form of a Planning Support System. Both approaches have strengths and limitations, and we will see how such approaches are adopted in actual urban models: SLEUTH and Metronamica (SLEUTH is more of a pure model without a module for data visualisation, but Metronamica has certain degrees of visualisation function).

The Value of Urban Models

As discussed before, the diversification of urban modelling styles has been well examined from a methodological viewpoint in a number of research works. However, why urban models as vehicles for planning support have experienced such paradigm changes has been less well explored. Since this also provides an important context for the use and development of urban growth simulation models, this research further summarises some important leverages that have affected the course of the development of urban models. These include critiques on traditional urban models, the changes in planning agenda, and the shifts in social attitude to scientific knowledge in policy making.

Firstly, early urban models faced some harsh critiques due to the practical limitations, and the constructive recognition of such criticism has clearly affected changes in urban modelling trends. The most influential critique of traditional urban models is the one made by Lee (1973), and it is worth looking at the original critique in detail. Lee argued that urban models in those times failed to meet their goals and pointed out the limitations of urban models, in terms of seven sins of large scale urban models. These arguments had an extensive effect on the general view of urban models - the usefulness of urban models for planning support was largely put in doubt. Though the validity of the critiques was also questioned by many researchers (Harris, 1994; Klosterman, 1994; Wegener, 1994), Lee's critical points below have stimulated the development and use of different styles of urban model. The seven points were:

- Hypercomprehensiveness: The models try to capture too many complex systems in a single shot and to serve too many goals at a time.
- Grossness: Whereas the models require extensive data, the details of model outcomes are too coarse to be useful for policy makers.
- Hungriness: Data requirements for the models are overwhelmingly large and heavy.
- Wrongheadedness: The claimed model behaviour and the equations that control model behaviour do not match. Besides, in most cases, the model structures are impossible to perceive and remain unknown.
- Complicatedness: Too many variables and interactions are taken into account.
- Mechanicalness: Model running requires the use of computers, but this is a time consuming and iterative process.
- Expensiveness: The cost of model building is too expensive and simply surpasses the cost of socially more valuable investments.

Secondly, the shift in urban planning and policy trends has also affected the development and use of urban models. As seen before, urban models originally emerged as practical inventions to test the impact of urban policies in the 1950's and 1960's. Such urban policies in those times were typically growth oriented ones which involved large public investments especially on transportation networks to facilitate suburban housing development. In those times, urban models were integrated with actual planning processes in order to provide relevant knowledge and information about urban systems such as future population, jobs, land uses, and traffic volumes. However, the main focus of recent urban development policy has changed from ‘growth support’ to ‘growth management’. In modern times, planning concerns in most developed countries lie more in managing urban sprawl, and urban growth is only considered desirable within the boundary of sustainability. While early urban models have strength in modelling the positive relationship between the transportation networks and urban systems, they are not ideal tools to study urban sprawl which occurs at a smaller spatial scale and in a non-linear manner. Complex science based cellular automata models and/or agent based models offer a better framework to study these types of urban problem. It is important to note that the focus of urban policy is continuously changing, and this provides an important impetus for the evolution of urban models. For instance, now urban planning is linked with an even broader agenda such as climate change, and it is not surprising to see new styles of urban models will be necessary to respond to this type of planning agenda.

Thirdly, urban models rely on scientific and quantitative methods, pursuing empirical objectivity. However, such beliefs are largely questioned in the social science field as well as in the planning field. While traditional urban models have been scientific problem solving tools, new styles of urban model, such as cellular automata and agent based models are seldom used to predict the impact of public policy. What has changed is not only the views about urban models *per se* but also the role of scientific knowledge in planning policy making. Traditional urban land use transportation models were responsive to outcomes of planning policy making in those times in which positivist thinking largely dominated the planning domain. Urban models were considered as a vehicle for scientific knowledge. Although such urban models are still used for planning (Environmental Protection Agency, 2000; Wegener, 1994), heavy reliance on instrumental rationality is no longer a major driving force in planning policy making, at least in the democratic plural societies. Even tested scientific knowledge has a limited role in contemporary communicative planning which heavily emphasises value-laden social interaction processes.

In summary, the shift in urban modelling styles is the outcome of interaction between methodological advancement and changes in urban planning and policy making. In this sense, urban models are not only scientific achievements but also social constructs. This explains the changing methods and roles of urban models over time. Comprehensiveness and operationality once was a good enough condition for scientific urban models (Wegener, 1994), but current disaggregate and dynamic urban models have a much more simplified model construction and a less clear link with practical policy. It is generally known that the practical link between urban models and policy making has weakened because of the various scales of reasoning presented in the above discussion. It is also clear that no urban models or support systems can capture the whole of a diversified modern planning process (see Figure 2.2). Although questions about whether the new style of urban models could have substantial links with policy making is a necessary one to answer, then another important question is to what extent those urban models could play a role in planning policy making. One answer to this is urban modelling as story telling (Batty and Torrens, 2005; Couclelis, 2005; Guhathakurta, 2002). Here urban models tell of possible futures and provide arenas for public discourse. The urban models can be virtual test beds to explore policy options and media to set shared visions for the desirable future state.

> "Urban models are more likely to be frameworks for assembling relevant information, frameworks for formal and informal dialogues where they are essential tools in much more consensual and participative processes of decision support". (Batty, 2009)

Regardless of different types and forms, urban models offer two key benefits. Firstly, urban models provide logical means to understand urban systems. To do so, models are typically built around an appropriate theoretical framework to capture the very nature of the system under study and then tested against real world data to examine their validity. Well established models are then applied for predicting futures. However, while theoretical simplification provides the essence of the system that is otherwise not easily seen in the real world, the omission of details about the real world is an inevitable and integral part of modelling. A potential tension between theory and practice does reside in models. Secondly, urban models provide a computer based virtual laboratory to examine the effects of various policy options and alternative futures. Urban models, which involve various data analysis and computation work, are essentially implemented in computer environments. Combined with varying assumptions and data inputs, urban models support the use of land development scenarios in support of planning policy making. Different land use scenarios can answer "what if?" questions by forecasting alternative futures under important influences and factors. The use of scenarios in an urban modelling context supports the analysis of the causes and consequences of future land use changes. By doing so, it then increases awareness of future consequences and supports long term strategic decision making. Policy makers and stakeholders can learn from possible outcome states in future without doing experiments in the real world.

Urban models, especially dynamic simulation models, can play a crucial role in understanding complex urban systems by delivering knowledge about the current and future state. Specific functions and supporting roles vary by individual models. The next chapter more specifically describes cellular automata and agent based urban simulation models which is the main modelling focus of this study.

Chapter 3: Notions of Cellular Automata Systems and Agent Based Models

3.1. Notions of Cellular Automata Models

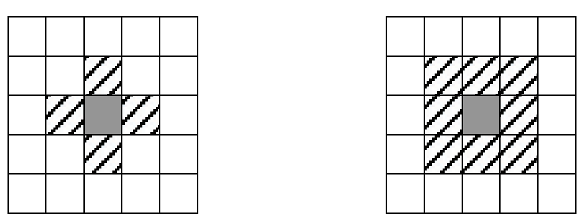
Cellular automata systems were originally designed to study self-replication in the natural sciences, originally as computable systems in general and then in fields such as biology and physics. The origin of cellular automata system traces back to the idea of the Turing machine invented by Alan Turing in the 1930's. But a more concrete form of cellular automata system was firstly developed by two mathematicians John von Neumann and Stanislaw Ulam during the 1940's and 1950's. Inspired by Ulam's suggestions, von Neumann built an abstract model of a self-replicating system which has 29 possible states as colours associated with complicated transition rules. The system was originally designed to emulate various mechanical devices and computing operations but since then the notion of cellular automata system has been tested and applied in a diverse range of situations. While essentially one dimensional cellular automata systems were studied for arithmetic and other related operations in the late 1950s and early 1960s, two dimensional cellular automata on a grid space generated more interest from the 1960's onward. After the widely known cellular automata model from John Conway's "Game of Life" was developed in the early 1970's, research into cellular automata systems has rapidly become popular from the 1980's (Wolfram, 2002).

A cellular automata system is a dynamic system which evolves over time. Automata arranged in a cell space form a basic computational unit of the cellular automata system, and individual automatons interact with their surrounding neighbours in the system. The cell has a finite number of state values or properties at a certain time point, and the state of each cell is updated at each discrete time step along with a predefined rule set. Consequently, the cell state is continuously updated at each time until the end of the model run. Dimensions of the cell space can vary: one, two, three, or more. Although diverse variations are theoretically and technically possible, typical cellular automata systems are structured in a two dimensional regular tessellated space on discrete time steps. Such a cellular automata system is generally defined by four elements: cells, cell states, neighbourhoods, and transition rules (Batty and Xie, 1997). In addition, the time step also can be considered as an essential element since it is a dynamic model (White and Engelen, 2000). Detailed descriptions of these five elements are as follows:

- Cell Space: A cell is a fundamental computational unit in the cellular space. While there is no particular restriction on their size and shape, the cells in the given space are usually homogeneous in size and shape but are heterogeneous in their attributes (cell states). A common form of cell is square in a rectangular grid space, but the cell also can be other shapes such as a triangle and hexagon in non-rectangular tessellations. The cells can be arranged in various types of space. Two-dimensional space is the most common configuration although one or three dimensional space is also possible. Such spaces can be either finite or infinite depending on the purpose of model. If the space is infinite and two dimensional, it is assumed that the top end is joined to the bottom end and the left end is joined to the right end. The opposite is also true.
- Cell State: Each cell in cellular space can hold a value or property for a certain time step. The cell itself is immobile but its state can be updateable over time. The simplest form of cell state is binary (e.g. "on" or "off" and "alive" or "dead") but can take more diverse forms and ranges. The cell state can be an ordinal, nominal, or continuous value. Whatever it is, the change in cell state is basically a matter of its own state and the states of its neighbours.
- Neighbourhood: Each cell in a cellular system can be a centre and have adjacent neighbouring cells. Definitions of "neighbourhoods" can vary. Two widely used

neighbourhood patterns are Von Neumann and Moore neighbourhoods (see Figure 3.1). While the former comprises four orthogonally adjacent cells, the latter includes eight surrounding cells. How a cell is affected by its neighbouring cells is decided by these different types of neighbourhood pattern.

- Transition Rule: Transition rules are the heart of cellular automata systems. While the neighbourhood configuration defines the physical ranges of influencing neighbours, the transition rules define the algorithm of how cells change their states in relation to the states of their neighbours. The transition rules set the necessary conditions for the transformation of one cell state to another cell state over a specific time step. The rules can be deterministic or stochastic. While both offer complex system behaviour from individual cell transitions, the stochastic approach adds more complexity in an individual cell's behaviour.
- Time Step: Since a cellular automata model is a dynamic model, it reveals system changes over different time steps. Thus, starting from initial arrangement, it continuously updates system behaviour until the end of the model run. In most cellular automata models, the time step is discrete and it represents one complete application of transition rules over all cell space and the resulting system changes. In the case of the abstract model, the time step does not necessarily correspond to the any real world time units. But in the case of the empirical model, it is matched to a certain time scale such as a day, month, or year.

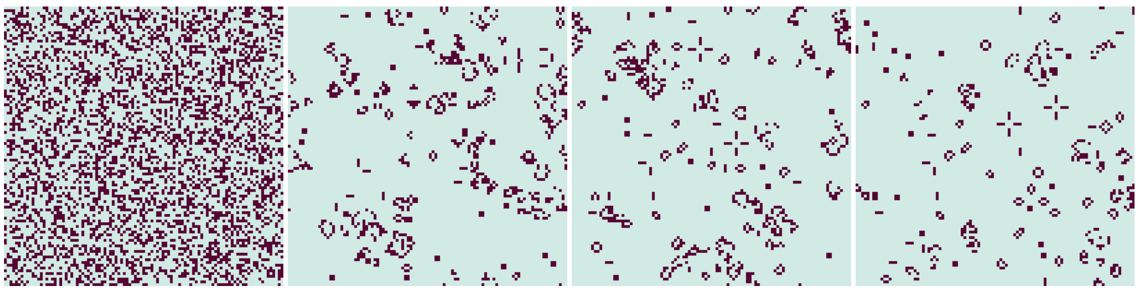


Von Neumann neighbourhood Moore Neighbourhood

Figure 3.1. Examples of Neighbourhoods

Along with the above elements, the following tasks are usually required to build and implement a cellular automata model: definition of the cellular space and the initial condition of the space, definition of the intended cell states, definition of a specific neighbourhood style, and establishment of the transition rules. To begin the simulation at the first time step (t), 'seed' cells are randomly or purposefully allocated in the cell space. The ways of setting the initial condition depend on the nature of the system under study. For instance, abstract cellular automata models such as the Game of Life model usually use random initial arrangements, but empirical cellular automata urban models like SLEUTH and Metronamica use cell based data to define initial conditions. It is also necessary to define the style of neighbourhood beforehand. The neighbourhood style defines a spatial boundary of the interaction between cells, and it also has an effect on the system behaviour. All cells individually process the predefined transition rules with reference to the neighbourhood defined, and then cell states are updated in the next time step (t+1). The process is continuously repeated for each time step (t+2, t+3, ... t+n) and finished at the scheduled time step or when necessary.

Although an automaton is the main unit of information processing and state change, the main focus of cellular automata systems lies in discovering hidden and complex system behaviours at a global level which emerge through changes in each automaton. The Game of Life model is the flagship cellular automata model which shows well such key characteristics of the cellular automata system. The model is configured in the following simple way. In a two dimensional grid space which contains a number of cells, each cell is in either of two possible states: alive or dead. At each discrete time step, each cell checks the states of its neighbours in the Moore neighbourhood configuration and then updates its state in the next time step based on the following simple rules: 1) A live cell with one or no live neighbours dies; 2) A live cell with two or three live neighbours stays alive; 3) A live cell with three or more live neighbours dies; 4) A dead cell with three live neighbours becomes live. Based on such simple rules, the system reveals very complex dynamic patterns as each cell changes its states. The initial condition is randomly generated but the system becomes stabilised in the long run. The system eventually reveals certain regularities such as glider guns depending on the initial arrangement of cells. The system behaviour of the Game of Life model is depicted in Figure 3.2.



t=0 t=125 t=250 t=500

Figure 3.2. The Game of Life Model

This cellular automata systems approach first came to the attention of geographers, particularly Tobler (1979), in the early 1970s where he saw the correspondence between the development of cellular automata by researchers such as Arthur Burke and John Holland at Michigan and his own work in cartographic representation. In this sense his paper on simulating Detroit (Tobler, 1970) launched the field, but it was not until the late 1970s that he first suggested that the geographic phenomenon could be translated into a cellular array and explored through cellular automata mechanisms based on neighbourhood types and transition rules (Tobler, 1979). Tobler suggested five types of model that explain dynamic land use change in a cell space. Some are not purely cellular automata but cell-space systems and thus closer to the kind of raster operations that one sees in GIS. Thus, these models offer important insights such as the integration of the principles of land use development based on the notion of cellular automata neighbourhoods with that based on GIS layers. The models proposed by Tobler (1979) can be described as follows:

$$c_{xy}^{t+\Delta t} \neq c_{xy}^{t} \tag{3.1}$$

$$c_{xy}^{t+\Delta t} = F(c_{xy}^{t}) \tag{3.2}$$

$$c_{xy}^{t+\Delta t} = F(c_{xy}^{t}, c_{xy}^{t-\Delta t}, c_{xy}^{t-2\Delta t}, \ldots, c_{xy}^{t-k\Delta t}) \tag{3.3}$$

$$c_{xy}^{t+\Delta t} = F(e_{xy}^{t}, f_{xy}^{t}, g_{xy}^{t}, \ldots, h_{xy}^{t}) \tag{3.4}$$

$$c_{xy}^{t+\Delta t} = F(c_{x\forall i, y\forall j}^{t}) \tag{3.5}$$

where c_{xy}^{t} is the land use category such as urban and rural at the cell location *x, y* at time *t*, and $c_{xy}^{t+\Delta t}$ is the land use category at the same location in the future. If Model 1 (equation 3.1) holds, this suggests an independent random land use change which has no relationship with previous land use at the spot. Model 2 (equation 3.2) simply notes that a land use change at location *x, y* at time $t+\Delta t$ functionally depends on the previous land use at that location. Model 3 (equation 3.3) defines historic land use change. Land use change in the future is a result of land use at that location in several previous time steps and this kind of model often appears in econometric formulations where variables at past time periods are lagged in time and influence. Model 4 (equation 3.4) proposes a multi variable (or layer) cellular operation. The land use depends on the several different additional factors at the same or at different locations. Model 5 (equation 3.5) suggests an application of a typical cellular automata system where land use depends on the land use of its neighbours in the previous time, that is where $x\forall i$ and $y\forall j$ represent the cell neighbours of x and y called i and j. Despite possible limitations such as the complexity of the actual geography, Tobler (1979) concluded that this approach makes possible the numerical study of non-numerical geographic change.

This new approach to the study of geographical representation began to influence urban modelling in the 1980's and soon it became a dominant paradigm. Couclelis (1985) first presented an hypothetical cellular automata model in an urban context, exploring how changes in individual cell states can represent large scale urban change. Couclelis demonstrated that a cellular automata urban model can be as simple as Conway's Game of Life model. For instance, a cell in a given space has two possible states: alive and dead. A live cell could be considered as an urban zone. Like the Game of Life model, the future state of an urban zone depends on the states of its neighbours. However, Couclelis also argued that the problem with such an abstract cellular automata model is that it is too simple and inadequate to explain real world spatial phenomena. In this vein, Couclelis called for a cellular model which combines theories to explain large scale urban changes resulting from local level conditions such as density. The development of new methods of urban morphology based on fractals provided a spur to the use of cellular automata for the generation of many fractal shapes across different scales is essentially based on the cellular automata algorithm (Batty and Longley, 1994). These developments were then followed by various proposals that cellular automata might be used for actual urban systems growth which in turn is based on the notion that urban growth is fractal. Combined with GIS, packaged cellular automata models focused on urban growth such as SLEUTH and Metronamica appeared in the mid to late 1990s with the cellular automata urban model becoming one of the most popular approaches to the study of contemporary urban systems. However, the cellular automata model has not simply remained as a new methodology. Linked to the complex sciences, it has provided a much broader knowledge framework in which to understand urban systems in terms of interactions between their components, their spatial structure, and their temporal dynamics (Batty, 2005).

The very power of the cellular automata model is the simplicity of its transition rules which gives rise to much richer resulting system behaviour than in other forms of model. Such complex system behaviour emerges from very simple local interactions between individual cells and this is the essence of emergence in terms of the way spatial patterns repeat themselves, in scaling self-similar fashion. As a proof of concept, before proceeding to the calibration of SLEUTH and Metronamica, we present a couple of abstract cellular automata models to demonstrate how simple local transition rules can be used to emulate complex urban growth. Furthermore, these examples also show how such basic patterns generated by simple local rules can be further augmented by global level rules which have an analogy with planning regulations and external investments.

Imagine a two dimensional grid space which contains a number of cells. Each cell has either of two possible states: urban or non-urban. Each cell checks the state of any cells which comprise its neighbours in its Moore (8 cell) neighbourhood in each time step and updates its own state in the next time step, dependent upon the status of its neighbourhood. Suppose that there is an initial urban centre composed of four urban cells. Let a vacant (non-urban) cell become an urban cell if three or more neighbouring cells are in the urban state. As shown in Figure 3.3, the resulting pattern is a mono-centric urban growth which is well explained in the domain of urban economics. However, note that what drives such growth here is not the decision-making of economic actors but simple interaction between cells. This clearly captures the strength of the neighbourhood effect in the cellular automata model.

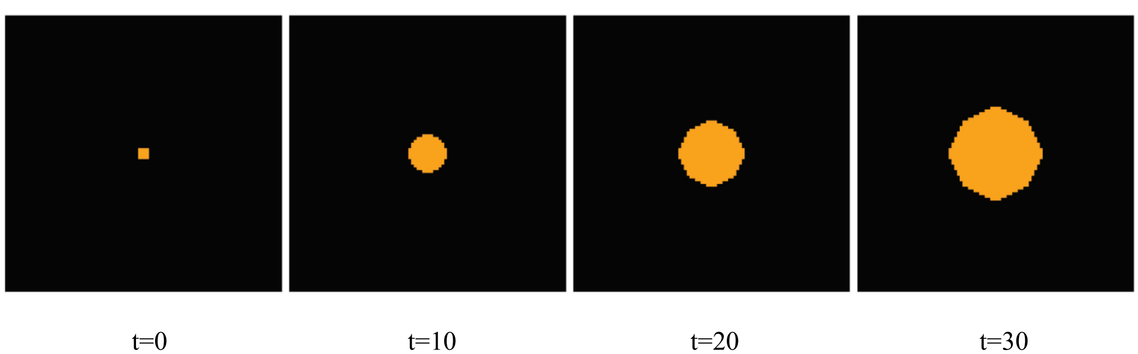


Figure 3.3. Simulation of Simple Concentric Urban Growth in a Cellular Automata System

Dynamic and heterogeneous spatial conditions can add more reality to the above model. The following simulation is run with the same initial conditions and transition rules, but let us now imagine a new town development on the left side of the growing urban cluster and a new park on the right side. Two such different entities are introduced at t=20 for this simulation. The new town itself is not growing although it is in an urban state since no cells in the boundary of the new town area have three or more urban cells in the Moore neighbourhood. The park is also static over time because the area does not contain live urban cells. However, the park is protected from urban development by global regulation while the new town is not protected since it is already urban. As the central urban cluster grows, these two urban clusters merge together forming a conurbation but the protected park area is not affected by ongoing urban growth. Figure 3.4 presents the sort of dynamic change that emerges in simulating such an urban growth system.

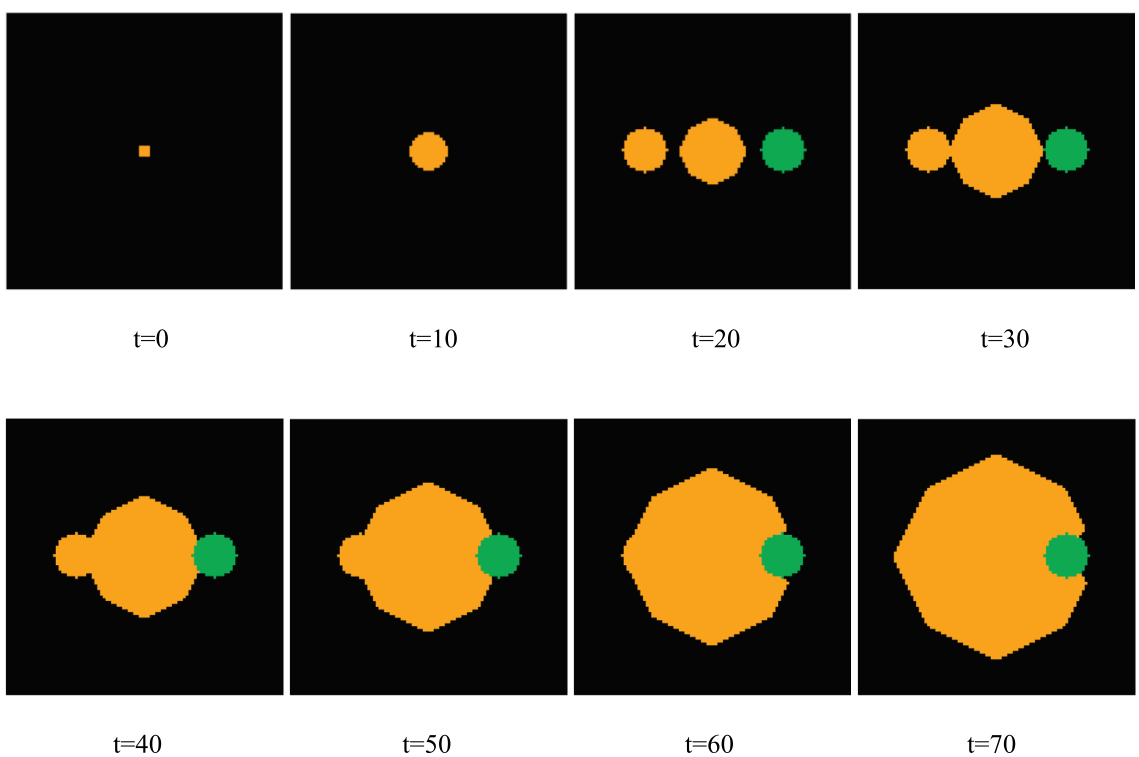


Figure 3.4. Simulation of Planned Development and Zoning Regulation

Now the following model assumes different initial conditions and transition rules. Let there be an urban core in the centre of the space and a road network in its four perpendicular directions, i.e. north, south, east and west. It is an *a priori* condition here which mimics these possible real world geographic features but it might mirror the dynamic introduction of a new transportation network if necessary. Let a vacant cell become urban if there is more than one urban cell in the neighbourhood but only when there is a road cell in the Moore neighbourhood at the same time. The result is a linear urban growth along with the road network as shown in Figure 3.5.

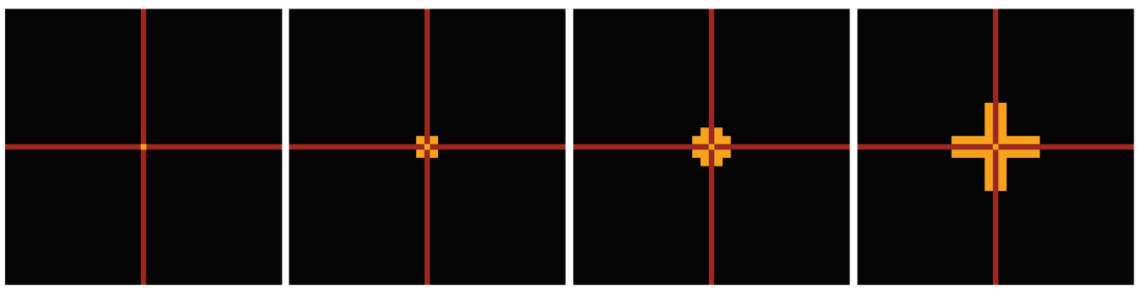


Figure 3.5. Simulation of Road Dependent Urban Growth

As seen through the above simulations, it is clear that the power of the cellular automata model lies in its ability to represent complex system behaviour from such simple local interactions between cells. This of course is the basis of simple diffusion but the discreteness of the lattice on which development is played out always leads to some symmetry-breaking of the rules when they are operated with some degree of random noise. The above mechanisms however can be the basic building blocks for developing a cellular automata urban model. However, simulating an actual urban system requires much richer methods and transition rules which depend on many *ad hoc* constraints and invariably stochastic cell transitions. Various modifications in defining cells, cell states, neighbourhoods, and transition rules are also possible and indeed necessary for modelling actual urban systems. The next section discusses how cellular automata systems are adapted and augmented to simulate urban systems.

3.2. Cellular Automata Models for Urban Systems

The value of early cellular automata models was seen in providing a pedagogical metaphor for simple abstract models. In such cases, cellular automata models are built upon the previously mentioned four basic elements. That is, cells are arranged in a grid space with either von Neumann or Moore neighbourhood configurations, and then a set of “if-then-else” style deterministic transition rules defines how cells change their states. Like Conway’s Game of Life model, these minimalistic configurations and transition rules can present rich system behaviour and present a meaningful metaphor for the study of urban systems. Such an ability to reveal complex system behaviour from simple local interaction is one of the key merits of the cellular automata modelling approach and enables various theoretical explorations of urban systems.

Since the cellular automata modelling approach has become popular in the urban modelling field from the 1980’s, this new urban modelling method has provided an effective way to study land use change and urban growth. Since the changes in urban systems occur in time and space, such disaggregate and dynamic modelling approaches have offered a useful framework for understanding land use change processes and patterns. Moreover, cellular automata based urban models have not just been built around pure notions of cellular automata systems for theoretical experiments but augmented with diverse methods for more practical applications. With various methodological developments and practical applications, cellular automata models are now among the main tools for modelling land use changes and urban growth systems (Benenson and Torrens, 2004).

However, such minimalistic approaches can provide useful insights but may not be adequate to encapsulate various urban phenomena. In order to capture more realistic urban system behaviour and to use cellular automata urban models for practical applications, diverse methods and techniques have been developed since the 1990's. As a result, different styles of cellular automata urban model have been developed to study urban systems. These models typically modify some basic elements of cellular automata systems and introduce different styles of cells, neighbourhoods, and transition rules. Furthermore, they also introduce external methods and techniques to better model urban systems. Among many examples and possibilities, some are described as follows.

Firstly, although most cellular automata urban models are predominantly built on a regular grid space, it is also possible to assume different shapes of automata. For instance, the use of irregular spatial units such as Voronoi polygons instead of regular grid cells is one way to better represent real world geography and to expand the cellular automata model. In this way, the interaction between various spatial objects, such as point, line, and polygon in irregular shape and size, can be taken into account in a cellular automata model (Shi and Pang, 2000). In a similar vein, recently Stevens and Dragicevic (2007) developed a cellular automata land use model which uses the land parcel as a basic spatial unit to model the interaction between different sizes and shapes of land parcels. However, these types of spatial tessellation are not yet common and much research effort has been on developing different neighbourhood styles and transition rules in a regular grid space.

Secondly, a notable modification to the classic cellular automata system is the use of different styles of neighbourhood. In a conventional von Neumann or Moore neighbourhood configuration, a cell is only affected by its immediately adjacent 4 or 8 cells. For instance, in the case of a pure cellular automata model, a cell in a particular state at a particular time step is only the result of the local dynamics of neighbouring cells. If only this logic is applied, the urban transition of any land use is just a function of the immediately surrounding land at the previous time step. Although it can produce meaningful system behaviour, this is hardly the case in a real urban system. The change of land use of course depends not only on the conditions of the local neighbourhood but also on the conditions of various global and other local factors. For an urban system, however, it is reasonable to assume a wider neighbourhood because the impact of urban development does not just reach the immediate surrounding areas. Thus such conventional neighbourhood configuration can be expanded by incorporating the notion of "action-at-a-distance."(Batty, Couclelis, and Eichen, 1997). In this way, a gradient effect of spatial relationship can be considered in the neighbourhood. White and Engelen (1993) proposed a large circular neighbourhood which includes all cells within a radius of six cells from the given cell. Then the distance decay effect was applied in the neighbourhood – i.e. all cells in the neighbourhood interact with each other, but closer cells get a stronger weight and relationship.

Thirdly, applying constraints to cell transition is another way to fit cellular automata models into practical applications (Phipps, 1989). For urban models, consideration of natural and institutional intervention is essential. Such constraints can be local, global, physical, or socio-economic. Whereas local constraints control single cells or certain areas, global constraints are applied to the entire cell space. At the same time, constraints can be physical or non-physical. Physical constraints have fixed locations over the cell space and control relevant cells. These types of constraint include slopes, road accessibility, and so on. Non-physical constraints on the other hand are certain conditions or coefficients that affect cell transition without having a fixed location on the cell space.

Fourthly, the most important influencing modification is the diversification of transition rules. One significant characteristic of the cellular automata model is system behaviour which emerges from very simple local interaction. Thus, in the case of the simple abstract cellular automata model, the transition rule is often minimalistic and deterministic. It does not necessarily need to be complex to capture whole system behaviour. However, since urban systems are influenced by diverse factors and environments, various transition rules have been developed in the effort to model urban systems. This ranges from simpler ones fundamentally built upon conventional cellular automata frameworks to more complex ones augmented by ranges of external methods. Since the core of the cellular automata model lies in the transition rules which define the process of system change, various cellular automata models are built on unique transition rules. Another way to add realistic system behaviour is introducing stochastic transition rules. Under deterministic rules, there is only one pre-determined transition to a next state for a given configuration. One the other hand, the cell transition is subject to random numbers and thresholds in a stochastic cellular automata model. This adds random disturbance to the system and enables realistic representation of complex urban systems.

Finally, it is also important to note that Geographic Information Systems (GIS) have played an important role in developing cellular automata urban models. Since the data model of raster GIS has interoperability with standard cellular space, cellular automata based urban models often take advantage of GIS data processing, analysis, and visualisation. Although GIS is external to cellular automata methods, the use of GIS is somehow an essential part of cellular automata urban modelling. The integration of GIS and cellular automata models typically takes the form of loose-coupling architecture. Since off-the-shelf GIS applications normally do not directly support cellular automata modelling and vice versa, the loosely coupled method is often the most efficient method of linking two methods. For instance, input data for cellular automata models can be prepared from GIS data processing, and output data from the models can be transferred to the GIS for further analysis and/or visualisation. Such a loose-coupling approach involves manual data transfers but facilitates flexible model development with various pre-existing GIS data infrastructure. Moreover, linking with GIS data enables modellers to use diverse empirical spatial data which is a key to the calibration and validation of cellular automata urban models.

All forms of the above methods and techniques appear in cellular automata urban models. Among many established cellular automata urban models, some are developed into generic modelling packages which are available free or at some cost. Particular attention is given here to two generic models: SLEUTH and Metronamica. SLEUTH, which is one of the most widely used cellular automata urban models, is built on fundamental principles of cellular automata behaviour of cell interaction but the model incorporates various statistical methods to produce realistic urban system behaviour (Clarke, Hoppen, and Gaydos, 1997; Clarke, Hoppen, and Gaydos, 1996). Metronamica, another pioneering cellular automata urban model, even alters certain core behaviour of the cellular automata system by introducing the notion of global constraints (White and Engelen, 1993; White, Engelen, and Uljee, 1997).

SLEUTH encapsulates key characteristics of urban land use change into a cellular automata framework. It is a classic example of how cell transition in a cellular automata framework can be translated and applied for modelling urban systems. Furthermore, the model introduces ranges of statistical methods to calibrate the model for practical application. On the other hand, Metronamica is more of a modified cellular automata model which incorporates the notion of distance decay and constrained transition. In the constrained cellular automata model, cell transition is not only governed by local interaction between cells but is also defined by exogenous constraints. In this model, each cell gets corresponding transition potential for state change based on the interaction between cells as well as other factors such as zoning. Then, the total number of cells allowed for transition is decided by an exogenous global constraint, and only limited numbers of cells are allowed for state change in each time step.

These models are amongst the most widely used cellular automata models and show the strength of cellular automata models as well as innovative methods unique to urban models.

These models have been applied to various case study areas ranging from small cities to large regions and proven to be effective tools for modelling urban growth and planning support (Clarke et al., 1997; Jantz, Goetz, Donato, and Claggett, 2010; Jantz, Goetz, and Shelley, 2004; Silva and Clarke, 2002, 2005; Stanilov and Batty, 2011; Van Delden, Escudero, Uljee, and Engelen, 2005; White et al., 1997; White, Straatman, and Engelen, 2004). These models are built upon fundamental cellular automata principles but hold additional methods such as global/local constraint, physical/non-physical constraint, stochastic processing, and GIS data integration. Thus the calibration of the SLEUTH and Metronamica models provide an opportunity to understand the key characteristics of cellular automata urban models in general as well as tools to understand the future growth of the study area.

We will demonstrate how cellular automata urban models can effectively simulate urban growth systems by augmenting the standard and generic models with various mechanisms and constraints which characterise the specification and calibration of the SLEUTH and Metronamica models. These comparisons will then give us the opportunity to develop further implications for the design and construction of cellular automata urban models in general. Full details of model behaviour and calibration results are given in Chapter 5 and Chapter 6.

3.3. Principles of Agent Based Models

Agent based modelling is a simulation method composed of agents that interact with each other and their environments. It is a computational modelling approach in that it takes the form of a computer program and in that there are inputs and outputs for the program. The program holds attributes of agents and environments and defines how agents act as well as the self-organising group processes of agent actions (Gilbert, 2008; Macy and Willer, 2002). Here on the conceptual level, the agents and environments are just generic terms describing their common characteristics, and there are no fixed definitions of them in terms of their forms, attributes, and behaviours. These are rather defined by the target systems of modelling, and thus there could be widely different operational definitions of agents and environments.

An agent based model shares some fundamental characteristics with a cellular automata system in that it basically consists of independent processing units and that it eventually exposes unexpected collective system behaviour from the interactions of those individual units. However, while cellular automata systems focus on self-reproduction, agent based models pay attention to self-adaptation. Thus an agent based model, as its name implies, focuses on the decision making behaviour of agents in the system. The one principal difference between a cellular automaton and an agent is the agent's autonomy in decision making and spatial mobility. Cellular automata are fixed in location and thus their neighbours are always fixed in space and time. During the entire time steps, an automaton only contacts the same and spatially fixed neighbours. In this sense, tessellated geometric shapes of cellular automata may bring efficiency in modelling spatially fixed features but may have limitations in capturing autonomous decision making entities in the real world. Agents on the other hand are not fixed in the cell space and are not confined to interaction with spatially fixed neighbours. In this way, it is possible to take account of social movement in addition to the physically surrounding neighbours. Thus agent based models can emphasise more realist interaction of autonomous units while cellular automata models merely focus on the transition of a cell's state.

The agent based modelling approach is rooted in the study of complex adaptive systems (CAS). A CAS is composed of active individual components, and the field of CAS typically focuses on their adaptation to a changing environment. The notion of CAS was motivated by the adaptation and emergence of biological systems. However, the scope of an agent based model has expanded beyond its origin in biological systems and it draws on many other related fields such as complex science, computer science, and systems science (North and Macal, 2007). It is also argued that agent based modelling is an essential epistemological component of complex thinking (Manson and O'Sullivan, 2006). Thus, it is not only the agent based modelling itself which provides such new perspectives on our world but also the larger intellectual domain of complex thinking. The direct intellectual influence behind agent based modelling is the study of complex adaptive systems. The notion of complex adaptive systems assumes that the system consists of heterogeneous and autonomous individual agents. The overall system behaviour arises from dynamic but local interactions of those agents. Naturally, another underlying notion of complex adaptive systems is that the systems are built from bottom-up. The study of complex adaptive systems usually concerns how self-organised complex behaviours arise among autonomous agents (Macal and North, 2006).

John Holland, a pioneer of complex adaptive systems study, identifies seven basic characteristics common to all complex adaptive systems (Holland, 1995). He suggests that CAS has four common properties and three mechanisms, and these characteristics of CAS provide a useful basis for understanding the nature of agent based models.

- Aggregation (Property): Interactions of individual agents lead to the emergence of complex large scale behaviour.
- Nonlinearity (Property): The whole system is greater than the simple sum of its parts. Linear extension of individual behaviours cannot hold the picture of the whole system.
- Flows (Property): A triad of node, connector, resource, which generally represents agent, interaction, information in turn, exists in complex adaptive systems. Flows over the network of nodes and connectors are not fixed in time. They are patterns reflecting the adaptive behaviour of connectors. Moreover, flows are subject to recycling effects and multiplier effects. Outputs of a certain node can be greater than inputs by internal processing, and resources passed from node to node can be increased by diverse value chains.

- Diversity (Property): Each agent is unique and has the possibility for its own interaction and specialisation. Besides, such diversity is dynamic in nature because it is the result of progressive adaptations – an agent learns from others and creates new interaction opportunities for others.
- Tagging (Mechanism): Agents are distinguishable from others, and this facilitates the formations of aggregates. Tag based interactions provide a basis for filtering, specialisation, and cooperation.
- Internal models (Mechanism): Agents have the power of anticipation. They have tacit models to infer desired futures and overt models to explore different alternatives.
- Building blocks (Mechanism): Internal models are composed of many reusable small building blocks. Numerous unique reactions are possible by combinations of different building blocks.

Like cellular automata systems, the agent based model is a dynamic system which evolves over time. While only the cell state is updated in each discrete time step in the cellular automata, the agent's attribute and/or cell state are updated in the agent based model. This depends on the types of agent based model. Certain agent based models only focus on the interaction between agents and resulting changes in agent behaviour. Other types of agent based models focus on the interaction between agent and environment. In this case, the agent may react to specific conditions in the environment or the environment changes as a result of agent action. Typical agent based models consist of the following components.

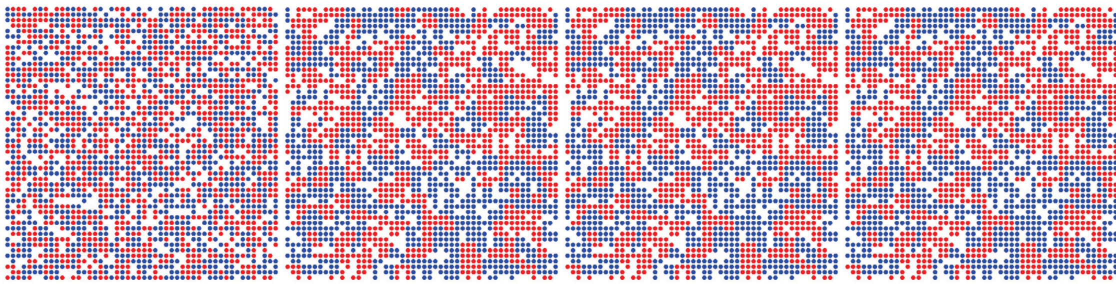
- The agent: It is the core element of an agent based model as the term implies. Although the nature and behaviour of agents vary in actual modelled systems, agents are typically described with the following common characteristics in terms of a general methodological viewpoint (Epstein, 2007; Gilbert, 2008; Miller and Page, 2007; North and Macal, 2007; Wooldridge and Jennings, 1995).

a. Autonomous: Agents act without top-down control. They are substantial units of decision making.
b. Proactive: Agents have their own goals and they make decisions on their own initiative.
c. Reactive: Agents are aware of their environments and react to their surroundings.
d. Interactive: Agents interact with neighbours and communicate with each other.
e. Adaptive: Agents are able to learn from other agents, and adapt their behaviours.
f. Heterogeneous: Agents have a unique identity and they act independently. No aggregate representation for agents is necessary.
g. Bounded rationality: Agents have bounded information and limited computational power.

- The environment: It is the cell space in which agents are placed. Although it does not have common characteristics, the environment can generally be divided into two types, conceptual and substantive, depending on whether it has an explicit relationship with agents or not. The former has no specific attributes and only provides an abstract context for agents' decision making. The environment in this case has no interaction with agents and it is static over time. The latter has its own cell states and it changes over the time either by its own defined characteristics or by certain agents' actions. The environment here affects agents' behaviour or is affected by agents.
- Agent attribute/Cell state: Each agent has its own characteristics and holds relevant attribute values. If interaction with the environment is necessary, state values can be assigned to the cell.

- Neighbourhood: When an agent makes a decision, it checks the condition of other agents or environments within its predefined neighbourhood. Like the cellular automata system, the two most common neighbourhood styles are the von Neumann and Moore neighbourhoods. However various alternatives are also possible.
- Agent decision making rules/Cell transition rules: The decision making rule of an agent governs overall system behaviour. It defines the way agent interacts with others and its environment. If the environment needs to be changed by itself or by an agent, relevant cell transition rules can be defined.

Like cellular automata systems, the agent based modelling approach also has its origins in the natural science field, but Schelling's (1971) residential segregation model, also known as Schelling's tipping point model, is conceived as the first agent based model which addressed social and spatial phenomenon. The economist Thomas Schelling studied racial preference and residential segregation by an agent based modelling approach. He firstly assumed a chess board as a city where different types of agents reside. The board is filled with two different types of coin which respectively represent different types of social group such as colour based on race. Each agent, coin, evaluates its status of happiness based on the types of its immediately surrounding neighbours and makes a decision about moving or staying. If the neighbourhood is occupied by the same type of agents above a certain number, the agent is happy and stays in the current location. If a different type of agent exists above a certain threshold, then the agent is unhappy and moves to a new location. The resulting pattern from this local level preference is a global level segregation which is depicted in Figure 3.6. Two types of agent are randomly placed in the space. Each agent checks and counts the type of its neighbours. If the agent finds fifty percent or more neighbours in the same type, it stays in the current location. Otherwise it moves to a new location in the next time step. The model shows that this style of simple preference can result in overall residential segregation. In a simple setting, the model reaches equilibrium at a certain time step and it becomes static beyond that point. If certain agents are periodically removed based on criteria such as life cycle, then the model can show evolving system behaviour over the time.



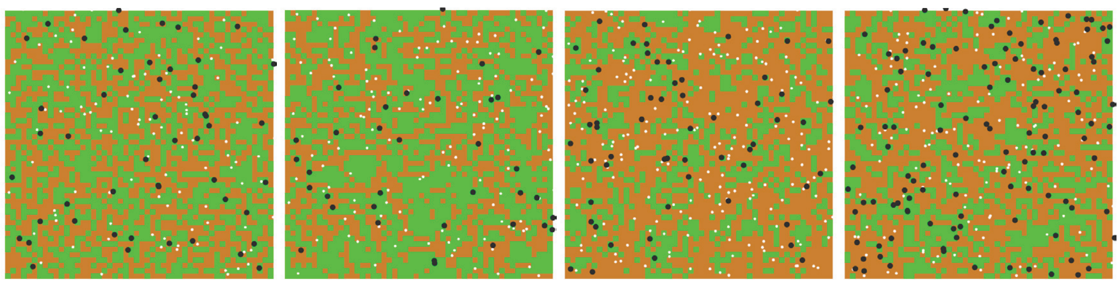
t=0 t=25 t=50 t=100

Figure 3.6. Schelling's Model of Spatial Segregation

The integration of existing theories into an agent based modelling framework is also possible. An agent based model version of the Lotka-Volterra model[6], commonly referred to as the predator and prey model, not only presents the possibility of such integration but also shows the interaction between agents as well as interaction between agent and environment. The original Lotka-Volterra equations explain the dynamics between two species, a predator and its prey, in an ecosystem. The model presents alternate growth and decline cycles of two species. In the model, the number of predators increase when there are sufficient prey. However, as the predator flourishes, the number of prey decreases. Such decrease in the number of prey eventually results in a decrease of predators. Then the decrease of predators stimulates the growth of prey again. The original model is non-spatial and built around a series of assumptions including one about their environment. The environment is indifferent for both species and prey

[6] The model consists of two differential equations that represent the growth of predator and prey over the time: $\frac{dx}{dt} = ax - bxy$ and $\frac{dy}{dt} = -iy + jxy$. Where *x, y* are the number of prey and predator respectively, and *a, b, i* and *j* are constants.

can find unlimited food elsewhere in the system, but such an assumption on the environment is released in the following example. The space consists of grass land and barren land. The grass has own life cycle, and the growth of prey not only depends on the number of predators but also relies on the availability of its food, grass. In this way, the number of predators is also affected by the changes in grass land. Figure 3.7 shows the system behaviour of the predator and prey model (The black and white dots indicate predators and prey, and the brown and green cells represent bare and grass land respectively).

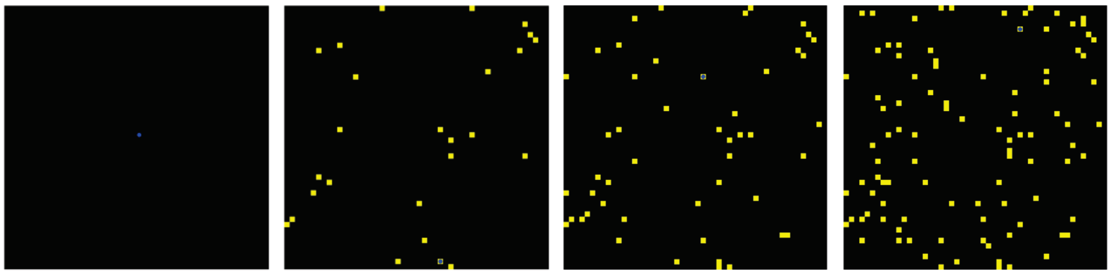


t=0 t=25 t=50 t=100

Figure 3.7. Predator and Prey Model in an Agent Based Modelling Framework

Like the extended predator prey model shown above, the interaction between agent and environment is necessary for agent based urban growth simulation models. In this way, the movement and location choice of an agent can be modelled as a main driving force of urban land use change and urban growth. As a proof of concept, the following abstract models are developed to demonstrate how an agent based model can be used to study urban growth systems. Suppose a household agent makes a residential location choice in the given space. Once the household is settled in a cell, the cell is converted as urban land. Then a new agent enters into the space to make a location choice. A key for this is the criteria of such a location choice, but an agent just randomly selects a cell in this example model. Figure 3.8 illustrates the simulation results of random movement and the resulting urban development by agents in the given space.

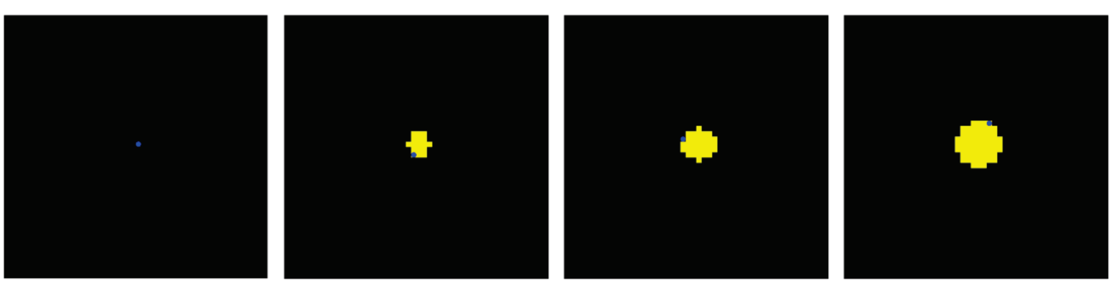
No rational decision making rule is yet given in this example, but such random urban development may have an analogy with small scale urban sprawl.



t=0 t=25 t=50 t=100

Figure 3.8. Agent's Random Location Choice

On the other hand, Figure 3.9 shows the results of households' preferences in a specific location. In this example, households simply want to be located as close to a central place as possible. The results are typical monocentric urban growth. A key difference between the agent based model and the cellular automata model is evident. While land use change is caused by the interaction between cells in the cellular automata systems, the land use change is a result of explicit decision making behaviour of agents in the case of the agent based modelling approach. Compare this simulation result with the concentric urban growth pattern generated by the cellular automata model which is shown in Figure 3.3.



t=0 t=25 t=50 t=100

Figure 3.9. Agent's Preference on Central Location

To summarise, the key notion of complex adaptive systems and agent based modelling is emergence, the term meaning globalised aggregate patterns arising from localised individual behaviours. The agents, elements of systems, are not static and passive but interact with other agents in the complex adaptive system. Then the agents adapt their behaviours to their surroundings. In this regard the whole system is not just a simple sum of its elements and is always greater than that. Agent based modelling is a useful and powerful method where the system is needed to be understood this way. It allows us to understand how individual actors shape the systems with or without top-down control and how the global regularity occurs and is sustained. However, agent based modelling differs from models built with conventional scientific methods. It is often referred to as a third way of doing social science, in addition to traditional inductive and deductive methods. Like deduction, agent based modelling starts from theories about the system of study and handles data about it. However, it does not prove the theories with observed data but generates data through experiments. Since such data does not come from the real world, it differs from induction. Because of these differences, it is called an instrument for generative social science (Epstein, 2007). The next section discusses how agent based modelling approaches can be used to simulate urban systems.

3.4. Agent Based Models for the Urban System

Agent based modelling as an approach to the study of land use change and urban growth is a relatively new idea, but it is also gaining in popularity in the urban modelling field. Although agent based modelling is an independent method, it is usually coupled with cell based models in the case of modelling land use and cover change (Parker, Berger, and Manson, 2002). Thus agent based models of land use and cover change are in fact integrated systems of two key components: agent based models and cellular models. The agent based model defines autonomous decision making entities and their decision rules for land use change. The cellular space defines certain land use types or landscapes in which those agents make their decisions. These two components act interdependently in that agents and their environments exchange feedback. This makes it possible to capture not only the interactions among agents but also between agents and their environment. Thus an agent based model integrated with a cellular model is a useful tool for the analysis of spatial processes, spatial interactions, and multi-scale phenomena (Parker, Manson, Janssen, Hoffmann, and Deadman, 2003). Both agent based models and cellular based models have their own potentials, but combinations of the two offer a unique approach to the study of urban land use change and growth systems. Although cellular automata models use transition rules to induce changes in cell states - e.g. land use changes, they have limitations in reflecting human decision making behaviour affecting those changes. On the other hand, an agent based model is not well fitted to handling diverse variables involving geographies or landscapes. While cellular automata models have merits in representing fixed geographies, agent based models have strengths in defining human actions over geographies.

An infusion of the agent based modelling concept into the cellular automata framework is the notion of Geographic Automata Systems (GAS) (Benenson and Torrens, 2004). GAS operates on the basic notion of cellular automata systems, but GAS distinguishes spatially fixed and non-fixed automata in the system. While an automaton is spatially fixed in a conventional cellular automata model, the GAS includes mobile automata which are controlled by relevant movement rules. Fixed automata can mimic geographically fixed objects such as roads or land parcels, and non-fixed automata can capture decision making entities like individuals or households. The GAS has movement rules for those non-fixed automata and imposes spatial relationships for them in addition to the four basic elements of cellular automata systems (Torrens and Benenson, 2005).

Torrens (2006) developed an agent based urban growth model of SprawlSim based on the concept of GAS. Cell transition, that is to say urbanisation, in SprawlSim is determined by the interaction between fixed and non-fixed automata. More precisely, two types of mobile automata, 'developed' and 'vacant' move around over the immobile automata by predefined movement rules. If a 'developed' mobile automaton occupies immobile automaton of a developable land state, then that immobile automaton is transformed to an urban land state. If a 'vacant' automaton settles on a previously urbanised automaton, then the cell is turned into vacant land being capable of becoming urban land in a future time step. Thus, unlike conventional cellular automata models, cell transition is determined not just by the condition of a static neighbourhood but by what occupies the cell. The model considers exogenous and endogenous influences in the form of model parameters and constraints. However, a unique characteristic of this model lies in the movement rules of mobile automata. The five rules define spatial ranges of possible movement and where the development and decay can take place: immediate, nearby, irregular, leap-frog, and road-like. An immediate movement rule defines the development process in its early stage. A mobile automaton only moves around in the eight adjacent cells of its Moore neighbourhood. Nearby movement mimics the large development practice.

The movement of the automaton is expanded to the 24 cells of its extended Moore neighbourhood. Irregular movement is introduced to represent development physically restricted by natural or man-made barriers such as mountains and administrative jurisdictions. Here the automaton's movement is confined to user-defined ranges and shapes. Leap-frog movement defines development taking place and in this case geographic automata are not confined to their surrounding neighbourhoods. Road-like movement represents construction of road networks, and automata in this case move along a single row or column. Non-fixed automata are attributed to human decision making entities that cause land use changes and urban development. However, those moveable automata are just vaguely assumed to be human decision making entities and the nature and characteristics of those decision making entities are not clearly defined. The model defines the ranges and types of movement but does not specify how mobile automata move and choose a location. The mobile automata basically move around randomly and are only restricted by constraints. In addition, treating 'developed' automata as a decision making entity is plausible, but assuming 'vacant' automata as a decision making entity is not. Moreover, mobile and non-mobile automata are logically distinguishable but unidentifiable in the cell space. In this sense, this model neither fully embodies the notion of an agent as a distinctive driver of system change nor efficiently takes account of human decision making behaviour. It is questionable whether this model is a new type of agent based model or a new extension of conventional cellular automata model combined with a different style of cells and cell transition rules.

SprawlSim is a good example showing how agent based modelling can be used for simulating urban growth, but agent based urban modelling is in its infancy and fully fledged generic models are not yet richly available compared to other types of urban model. Thus it is hard to use an established agent based urban model for an intended study area. Nonetheless, there are different ways to understand the purpose of agent based models. For instance, Axelrod and Tesfatsion (2006) define four types of agent based model: empirical, normative, heuristic, and methodological. The empirical approach seeks to answer why particular large-scale regularities have emerged and persisted without prominent top-down control. These types of agent based model can seek causal explanations grounded in the interactions of agents operating in specified environments. The normative approach seeks to answer how agent-based models can be used as laboratories to discover outcomes of designed agents and/or the environment. These types of models are interested in evaluating whether artificial designs will result in desirable system performance over time. The heuristic approach seeks to answer how greater insight can be attained about the fundamental causal mechanisms in social systems. These models focus on discovering the large-scale complex effects resulting from relatively simple and many interacting agents. The methodological approach seeks ways to advance agent based modelling itself. Rather than focusing on a system of interest, these models try to develop modelling principles and practical tools to implement agent based modelling. In a similar vein, Couclelis (2002) elaborates four possible types of agent based land use change model conditioned by whether agents and environments are designed or analysed. Details are given in Table 3.1 below.

Table 3.1. Different Types of Agent Based Urban Models

<table>
<tr><th></th><th></th><th colspan="2">Agent</th></tr>
<tr><th></th><th></th><th>Designed</th><th>Analysed</th></tr>
<tr><td rowspan="2">Environment</td><td>Designed</td><td>· Purpose/Intent
- Discovery of new relationship
- Existence proof

· Pros
- Social laboratories

· Cons
- Abstract</td><td>· Purpose/Intent
- Role-playing games among stakeholders
- Laboratory experiments

· Pros
- Behavioural experiments

Cons
- Complex of real decision making</td></tr>
<tr><td>Analysed</td><td>· Purpose/Intent
- Explanation

· Pros
- Problem-solving

· Cons
- Complex of real environment</td><td>· Purpose/Intent
- Explanation
- Projection
- Scenario analysis

· Pros
- Traditionally ‘scientific’

· Cons
- Hard to implement</td></tr>
</table>

Adapted from (Couclelis, 2002).

Designed agents have intentionally defined attributes and behaviours to prove purposeful concepts while analysed agents have observed attributes and behaviours representing those in the real world. The same goes for the environment. The combinations are:

- Both agent and environment designed: These types of agent based models can be used as virtual social laboratories to discover and understand hypotheses, but such discoveries are too abstract and only valid in artificial settings.
- Agent designed and environment analysed: These models are problem solving applications where agents are designed to operate within the pre-existing environment. They are useful for process based explanations of environmental changes but have limitations in representing complex real environments.
- Agent analysed and environment designed: These models can be used for understanding behavioural characteristics of agents in controlled laboratory conditions, but representing agent behaviour in the real world comes into question here.
- Both agent and environment analysed: These types are considered as 'scientific' from a traditional viewpoint. The models can be descriptive, explanatory, or predictive, but it is hard to implement them.

Such agent based models of land use change and urban growth offer some advantages over other types of land use change models: representation of various decision making players in land use change, representation of spatially explicit local interactions and decision making, representation of interdependency of human actions and environmental changes, and the ability to model the system response to exogenous influences such as policy and institutional changes (Parker et al., 2002).

In addition to the general characteristics of different agent based models, it is necessary to understand the strength and weakness of agent based models in a broader perspective in order to use them for policy support. The evaluation of strengths and weaknesses of agent based models can be tackled from different angles because the method combines distinctive elements and traditions. Previous research on the inventory of agent based models for land use and cover change discusses the trends of agent based urban models within various categories (Matthews, Gilbert, Roach, Polhill, and Gotts, 2007; Parker et al., 2002), but this research further discusses the advantages and limitations of agent based models in three different respects: their own methodological characteristics, inherited characteristics from computer simulation models, and inherited characteristics from complex systems models.

Firstly, the most significant methodological strength of an agent based model is its ability to consider heterogeneous individual decision making units and their interactions. When it comes to modelling human society, these characteristics can be matched adequately to the neoclassical economic type of thinking such as methodological individualism, bounded rationality, random utility maximisation, and so on. Thus agent based models of land use change have strengths in representing autonomous actors affecting land use changes in a bottom-up and market-driven manner rather than depending on a Keynesian top-down public investment approach.

Possible inconsistencies exist here as there are always “prisoner’s dilemma” situations in planning policy making (Voogd, 2001). Because individuals or organisations pursuing self-interest often do not make choices for socially desirable outcomes, the need for public policy intervention in varying degrees is almost always justified. Then the question is whether the agent based models, which fundamentally rely on behavioural rules applied to individual decision making units, are suitable tools to consider the influences of public policy options. Indeed, due to the intrinsic nature of agent based models, there is a difficulty of incorporating various planning policy options into the models. Although it is not impossible, only limited types of planning policy scenarios may be integrated into such models. If it is considered that planning policies often act as global and local constraints which regulate the input of ‘rational individual choices’ on land use systems, it is possible to model some policy options and scenarios in this manner.

Another concern lies in the capability of agent based models to capture individual human behaviour. When it comes to modelling natural world phenomena such as flocking birds, there is no doubt that agent based modelling is a unique and promising method to explore the complex nature of a system since such a decision making entity in the natural world has a simpler decision making behaviour. The problem is its applicability to the human world. Not surprisingly human decision making behaviour is literally much more complex than the behaviour of any decision making entity in the natural world. Human decision making is not only affected by locally contacted neighbours but also motivated by personality, education, social rank, mass media, social institution, and many other factors. Taking all these into account is simply impossible and may be inappropriate for any modelling purpose. Reductionism of agent behaviour is inevitable in this regard, and this is one limitation of developing agent based models. How to encapsulate the essence of agent decision making behaviour is a crucial key to developing an agent based urban model.

Secondly, since agent based models are computational simulation models, they can act like virtual laboratories which facilitate building various "what if?" scenarios and enable us to explore possible future states. The use of simulation models can vary. Training and education in real world like situations are typical applications, but the models also serve to improve target systems themselves in the real world by manipulating variables and investigating alternative outcomes. In any case, the key issue of a computer simulation model lies in its validation. Whether model outcomes sufficiently mirror the actual system behaviours are all important. However, agent based models have limitations on model validation because data about disaggregate individual entities are often unavailable. Thus their generative outcomes are often explorative rather than predictive. The strength and weakness of agent based models as computer simulations stem from the generative nature of model outcomes and the lack of model validation measures.

Conventional model building starts from the application of proven theories of the system under study. In this way, models can have a logical framework, relevant variables, and sound causal relationships between variables. Then the models are tested and validated by using empirical data. Conversely, models also can be used to construct hypotheses, followed by test and validation with real world data. However, although technically possible, it is hard to fit agent based modelling to this conventional process. There is a lack of land use change theories that agent based models can rely on, and it is also extremely difficult to validate the outcomes of agent based models. This narrows the practical standing point of agent based urban models. Models developed without established theory imply that the model does not stand on a refined knowledge framework of the system, and the use of models without validation raises a question about their practical applicability for real world situations. Thus the frequently claimed merit of being a 'virtual laboratory' is ony a partial benefit if the model lacks explanatory power.

Thirdly, agent based models inherit the complex systems notion of emergence. Rooted in the same idea, agent based land use models usually pursue the discovery of hidden and unexpected spatial patterns and processes resulting from the interactions of individual decision making entities. By nature, the focus is on the effect of bottom-up interactions rather than impacts of top-down actions. This has never been achieved in traditional urban modelling methods, and it definitely offers a new way of understanding and modelling urban systems. However, the bottom-up approach and the notion of emergence results in a heuristic approach to model outcomes. Since it often assumes the absence of global control, agent based land use models typically aim at discovering unexpected spatial behaviours at an aggregate level. Such heuristic modelling approaches raise a question about their fitness to planning practice, which involves intentional policy intervention and coordination. Brömmelstroet (2009) in this sense criticises such urban models for being based on heuristic algorithms that do not coincide with daily planning practices and its instruments. In a similar vein, Manson and O'Sullivan (2006) also point out a limitation of the "Let's see what happens" approach in complex modelling.

The crucial question is the use of agent based urban models. It is suggested that the use of agent based land use models can include a variety of applications such as policy analysis and planning, participatory modelling, explaining spatial patterns of land use or settlement, testing social science concepts, and explaining land use functions (Matthews et al., 2007). But from the literature review, this thesis sees that the use of agent based land use models is more appropriate in an explorative fashion for developing a knowledge framework than as operational decision support tools for generating analytical alternatives. Agent based modelling has the potential to be a more rigorous scientific tool, but currently it is largely confined by unresolved methodological and practical problems such as the pursuit of heuristic discovery, the difficulty of defining independent variables (model parameters), validating model outcomes, and so on.

Urban modelling relies on scientific principles, but urban policy making also relies on a social value system. Although conventional urban models treat planning policy making as a well-articulated and linear activity, urban policy making in modern times occurs in a much more volatile and non-linear context. Urban policy making is a complex interaction of different interests among multiple players and participants. For this reason, there is an inevitable gap between model and policy. With increased interdependencies and limited institutional resources, urban planning policy making is now a matter of intense collaboration and communication. The current dominance of collaborative planning policy making delineates the changed policy making context. At the same time, the main agenda for urban planning policy has changed from 'growth' to 'sustainability'. Under development oriented urban policies, the main interest of conventional urban models lies in testing the impact of public investment such as transportation networks. Such models do not attempt to understand the complex nature of urban systems but only take account of selected variables as a consequence of urban planning policy. However, under the sustainability oriented policy, the focus is more on restrictions and regulations. Clearly modern planning at a statutory and operational level consists of regulations and restrictions rather than investments and incentives. Planning often has strong interventional power to prevent undesired actions but lacks direct resources to realise desired futures. To achieve macro policy goals and visions, planning rather relies on partnership with relevant participants and stakeholders.

Agent based urban models are typically non-equilibrium seeking simulation models and this gives them an opportunity to discover unknown urban system behaviour. However, agent based land use models are not yet efficient tools to measure the impact of public investment especially in monetary or numerical values. Instead, agent based models of land use change and urban growth are relevant tools to explore possible urban futures resulting from a spontaneous self-organising process. They are more suitable as a broader consensus building tool to understand the impact of planning regulations on individuals, groups, cities, and regions. They are rather suitable for exploring possible outcome states of regulatory planning policies and discovering otherwise undiscoverable spatial patterns and processes. Although there is a limitation on capturing various policy measures, it is still possible to test the impact of planning policy choices as global or local constraints. Besides, as a dynamic modelling approach, agent based land use change and urban growth models are a promising method to inform the complex causes, processes, and future outcome states of urban systems.

The remaining question is how much can we rely on this type of new model and science. Crooks, Castle, and Batty (2008) point out the potential pitfall of arbitrariness in agent based modelling due to the lack of applicable theory, difficulty with validation, and so on. This research does not have a conclusion for this issue yet, but it will seek the integration of microeconomic location theories to better explain the decision making behaviour of the intended agent based urban growth model. Full details about this are covered in Chapter 7.

3.5. Toolkits for Cellular Automata and Agent Based Models

Developing a cellular automata or agent based model requires two broad research efforts: the design of a model structure and system behaviour and the implementation of the modelled system as a computer program. The former firstly requires substantial knowledge and information on the system under study. The nature of agents and their interactions with each other and their environment all depend on how we understand and encapsulate the system. Then the latter involves implementation of such a logical structure in a concrete form of computational program. Without creating the model as a computer program, the body of knowledge will remain abstract. Thus building an agent based urban growth model not only requires the definition of model structure and system behaviour for the target system but also demands an agent based modelling specific computer programming technique. The development of an agent based model in this section focuses on the computational implementation necessary for the model development.

First of all, the development of agent based models can be achieved by using conventional computer programming languages such as C and Java, but this requires extensive programming work of less relevance to the nature of system behaviour. Knowledge about an object-oriented programming language[7] is particularly useful for the development of agent based models. Modelling through such programming efforts may offer a flexible and dedicated way of model development, but it may require additional time and cost for the application development to deal with input data processing, user interface, output visualisation, and so on.

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[7] Object-oriented programming is a recent paradigm of computer programming which defines data and functions as objects. Reusability is one of the main advantages of the object oriented programming approach over conventional programming approaches such as procedural programming. It enables the programmer to create a program with interrelated modules that can be easily modified and adapted.

On the other hand, the development of an agent based model with dedicated modelling toolkits can reduce such burdens. Although many of them still require the use of specific programming languages to actually build the model, they provide ranges of common templates and building blocks associated with the implementation of agent based models in order to facilitate efficient model development. To this end, a robust number of agent based modelling specific toolkits have been developed including both proprietary and non-proprietary solutions. More than 50 toolkits are available at the time of research[8]. Some are designed for experts in specific domains while some target entry-level general users. A comprehensive and detailed comparison of agent based modelling toolkits has also been conducted (Nikolai and Madey, 2009). The authors examine various toolkits with a focus on the five key aspects: programming language, required operating system, license type, targeted domain of use, and user support. No particular judgments or recommendations are made, since none of them have absolute superiority over others. But the research provides a useful quick look over diverse agent based modelling toolkits.

Such a comprehensive review of agent based modelling toolkits is not the main interest of this research, but a narrow comparison is necessary in order to choose an appropriate development toolkit. Some toolkits are particularly popular among social scientists who usually do not have strong computer programming skills and opt for easy implementation. NetLogo is one of the most widely used toolkits for this purpose, but this type of toolkit has limitations in designing complex model behaviour. On the other hand, certain modelling frameworks like Swarm offer more functionality but these toolkits require a substantial amount of effort to understand the toolkits themselves. Among many available solutions, this research briefly compares the characteristics of NetLogo, Repast, and Swarm which are widely used for the

[8] http://en.wikipedia.org/wiki/Comparison_of_agent-based_modelling_software

development of agent based models in social science fields. Then greater attention will be given to Repast which is the intended agent based modelling toolkit for this research.

NetLogo was developed by Uri Wilensky at Northwestern University. It is an upgraded replacement of StarLogoT. With its own programming language, StarLogo's integrated compiler and interpreter provides one of the easiest approaches to the implementation of agent based models. Extensive documentation and tutorials as well as a large number of sample models are available. Thus, with a relatively easy-to-learn programming language and good user support NetLogo is a good solution for beginners but it shows limitations on functionality and performance. So it is usually used to develop simple and small scale models.

On the other hand, Swarm aims to support a more advanced level of model development. It was developed to facilitate complex science study at the Santa Fe Institute. The purpose is to help scientists reduce time consuming but unimportant computer application development tasks. The software consists of code libraries written in objective-C and Java. Despite good performance and modelling support, it has a very steep learning curve if it is compared to other agent based modelling toolkits. Besides it has limitations in using GIS data which is an essential element for many empirical urban models.

Repast (REcursive Porous Agent Simulation Toolkit) was developed at the University of Chicago (North, Collier, and Vos, 2006; North, Howe, Collier, and Vos, 2007). It is a free and open source toolkit and provides a good linkage with 2D and 3D GIS. This provides a fundamental advantage in building a spatially explicit agent based model with loose or tight coupling[9] with other geospatial applications. Repast Simphony, the newest version of Repast at the current time, offers a graphical user interface (GUI) based modelling environment with an integration of Groovy language. This enables instant and easy model development, but it has

[9] For instance, an agent based model in Repast can be integrated with NASA's World Wind web map application although it requires additional programming work.

limitations when developing more sophisticated models. So Repast also supports a direct programming interface with the Java language for more flexible model development. Java is one of the most widely used object oriented programming languages which provides a platform independent environment for developing and deploying computer application software in a wide variety of computing platforms and operating systems.

In addition, to further facilitate such programming tasks, Repast Simphony is actually embedded in a Java IDE (Integrated Development Environment). Java IDE is a kind of programming platform that facilitates the Java application programming process. It helps developers write programming code more easily by providing functions like auto completion and correction and it runs the codes more efficiently by integrating the JDK compiler and interpreter into its development environment. There are ranges of Java IDEs such as NetBeans, JCreator, and so on. Among many, Repast Simphony is equipped with Eclipse IDE. Eclipse is also a widely used toolkit for Java programming, so it can be said that Repast Simphony is a 'double-decked' agent based modelling toolkit with one for agent based modelling specific environment and the other for Java programming.

Table 3.2. Comparison of Selected Non-proprietary Agent Based Modelling Toolkits

	NetLogo	**Repast**	**Swarm**
License	Free, but not open source	Free, open source	General Public License
Modelling Language	NetLogo	Java, Groovy	Objective-C, Java
Ease of Learning and Programming	Good	Moderate	Poor
Speed of Execution	Moderate	Fast	Moderate
Link to GIS	No	Yes	No
3D Capability	Yes	Yes	No

Adapted from (Gilbert, 2008)

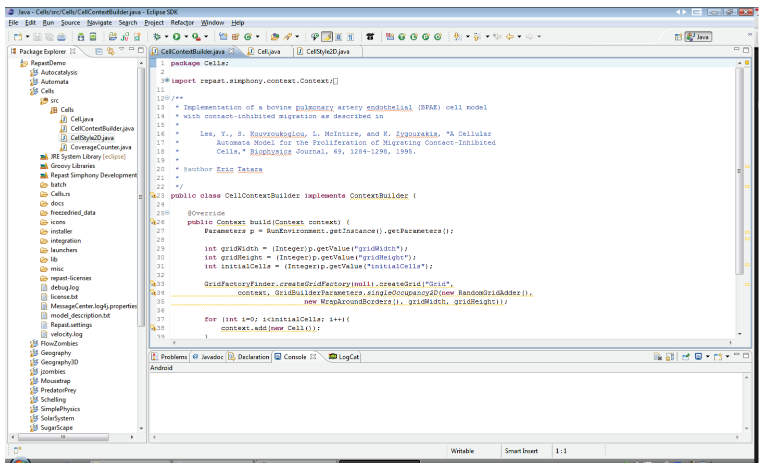
Among the above agent based modelling toolkits, Repast provides overall satisfaction for the purpose of this research. Table 3.2 summarises the key characteristics of NetLogo, Repast, and Swarm.

Figure 3.10 illustrates (a) the model development environment and (b) the GUI based model implementation interface of the Repast Simphony Java version. The model development environment is predominantly that of Eclipse which facilitates Java code writing, but Repast provides a set of Java class libraries which can be used to design the model. The library of classes provides a range of features such as ways to create agents and their environment, methods to schedule agents' interaction with others and/or environment, and tools to visualise simulation runs and collect the results. Rather than reinventing the wheel, such features allow modellers to focus on indigenous modelling works. Once a model is defined, Repast provides two options for running a model: batch run and GUI run. A batch-run simulation reads in an XML[10] formatted parameter file which entails the starting and ending values of its model parameters, the necessary increment to these parameters, and the number of runs to complete. In this case, the simulation can be started from the command line of Eclipse. On the other hand, a GUI run requires a user to start and stop a simulation through a graphical user interface and allows the user to set starting parameters in the GUI. The simulation can be run from a specially designed display window of Repast. The former has the advantage in creating multiple simulation results with varying parameter sets, and the latter has merit in visualising a dynamic process of simulation.

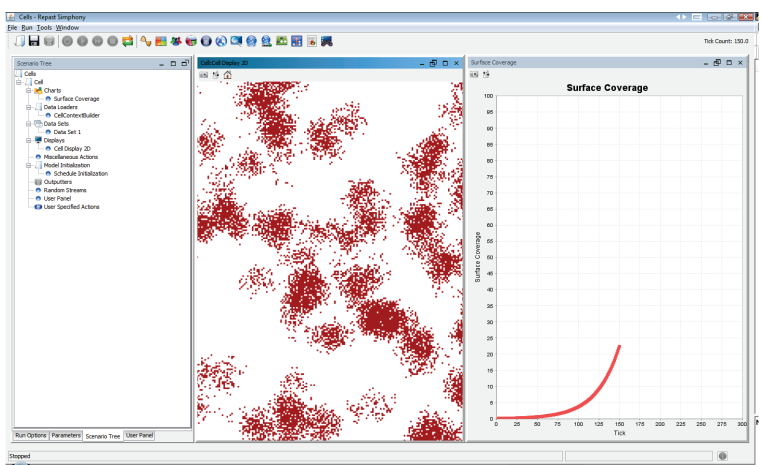
Most researchers in social science fields usually do not have formal education in computer programming whereas they are systematically exposed to other quantitative methods such as statistics and mathematics. So computer programming is still an alien research tool in

[10] Extensible Markup Language (XML) is a programming language especially designed to store and transfer data for the Web.

most social science fields, and this may act as an entry barrier to computational modelling in the study of social science. Although the use of an agent based modelling toolkit does not eliminate the need for programming, it mitigates the burdens of programming which is not the main focus of model building. In this way, the use of agent based modelling toolkits lowers such a barrier and indeed the author of this thesis also has benefited from the use of such an agent based modelling toolkit, Repast.



(a) Model Development Environment



(b) GUI based Runtime Interface

Figure 3.10. The Model Development and Runtime Interface of Repast Simphony Java

3.6. The Value of Complex Science Based Urban Simulation Models

Urban growth is one of the most important policy agendas in contemporary planning. Since planning policy requires knowledge about future urban states, the use of dynamic urban growth models enables planners to explore various 'what-if' scenarios. Simulation models of urban growth inform the planning process and support sustainable urban development through a scientific understanding of urban systems. In order to better model the urban growth system, this section discusses the key characteristics of urban growth systems and the strength and limitations of complex science urban models.

Urban growth first of all involves an expansion of the urban built-up area from a physical perspective, resulting in a spread of the urban fabric into the non-urban fringe area. In a nutshell, an urban system grows through centripetal and centrifugal forces which eventually result in urban concentration and deconcentration. Thus, urban growth models encapsulate the growth process through the dual processes of agglomeration and dispersion which can be observed in the form of land uses (Batty and Xie, 2005). From a functional perspective, urban growth can be regarded as changes in land use such as the conversion of agricultural land into residential use. Thus the study of urban growth has a direct relationship with land use and land cover change modelling and substantially falls into the same category in a broad sense. However, although land use and land cover change[11] models are capable of explaining urban growth patterns and processes, dedicated urban growth models pay more attention to the aggregate or dispersed occurrence of the urban built-up area than to the detailed functional changes of urban

[11] It is useful to clarify the difference between land use and land cover at this point. Whereas the former term denotes the socially designated purpose of a given land, the latter term indicates bio-physical characteristics of the surface of the earth. But in the case of urban growth modelling, the two terms are often being used interchangeably because the urban land use area usually corresponds to the urban built-up area. For this reason, this research does not strictly distinguish land use and land cover for the study of urban growth.

land use. However, at the same time, urban growth is a result of various interacting forces and factors – population migration and natural increase, public investment on transportation infrastructure, economic growth and the provision of jobs, housing development, spatial and non-spatial policy incentives and regulations, spontaneous individual rational choices, and so on. Thus there has been a wide range of approaches to capture the causes and forces of urban land use change and urban growth since such aspects can be investigated and modelled from various angles. As a result, different urban theories and models have been developed to highlight the different nature of urban growth systems to date, including statistical and econometric models, spatial interaction models, optimisation models, and so on (Briassoulis, 2000).

Although there is no one best way to model urban growth systems, it is important to note that the urban growth pattern itself and our understanding of urban structure has changed over time. For instance, urban growth has been traditionally understood as a spatial agglomeration of economic activities and resulting spatial concentration in an urban area. In this case, a formation and multiplication of urban concentration is a dominant form of urban growth. However, dispersed urban development, suburbanisation and/or urban sprawl, has also become a significant urban growth form in modern times. In this context, while early urban growth models focused on equilibrium outcomes produced from mathematical equations, recent efforts focus more on the changing nature of urban systems generated from complex theory and method (Batty and Xie, 2005). Since urban growth occurs in time and space, spatially explicit and dynamic modelling gains popularity as an effective modelling approach to understand such growth processes. At the same time, urban growth is increasingly studied as a disaggregate approach due to the characteristics of the ‘bottom up’ and ‘self-organising’ behaviour of contemporary urban systems. To this end, a newly emerging complex science brings valuable insights into understanding urban systems as well as planning policy. This complex science based thinking is a new infusion to urban modelling, and it is best achieved by dynamic and disaggregate modelling methods such as cellular automata and agent based models. However, since complex science is often called a new kind of science which differs from conventional scientific methods, it is necessary to discuss its nature and implication for urban modelling and planning policy making before conducting the calibration of generic cellular automata urban models and building the intended agent based urban growth simulation model.

Complex science is a new paradigm that extends or overcomes traditional Newtonian determinism in the natural sciences. Scientific determinism is a large intellectual domain of scientific philosophy. Although full detail cannot be explained in a nutshell, it is usually assumed that the world and its components are systematically ordered in coherent mechanisms. Systems under study are generally treated as linear systems, and thus the system behaviours are predictable if the constructing mechanisms are known. Contrary to such determinism, non-linearity and hence uncertainty portray the complex of such systems. Yet there is no universal definition and scope for complex science since complex science is a juxtaposition of various theories and practices from diverse fields. The domain is a breakthrough in normal science and an incremental accumulation of related findings and ideas. Turing's morphogenesis, Lorenz's butterfly effect, and Mandelbrot's fractals have all contributed to the formation of what is now called complex science or complex thinking. In a more rigid sense, the term "complex adaptive system" is coined by Holland (1995), and relevant characteristics are explored. Details about complex adaptive systems have been reviewed in conjunction with the notions of agent based modelling in the previous section.

This idea of complex science was firstly arrived at in the urban planning domain as a new methodology using cellular automata models to capture large scale urban phenomenon from micro scale local interactions. As discussed before, Couclelis (1985) explored how changes in individual cell states can represent large scale urban changes. Although cellular automata models have known strengths for the study of urban systems and constitute one of the most widely applied dynamic and disaggregate urban modelling methods, agent based modelling has gained an importance as a way of studying complex urban systems. Since agent based modelling more explicitly treats individual units or elements of systems as autonomous decision making actors and reveals unexpected system behaviour resulting from the interactions of individual actors, it provides much richer implications for human society and group decision making. Like urban models as a whole, the most widely used area of agent based models in the urban planning field is the study of land use systems. As a complex model of land use changes, it takes account of complex causes and processes and produces model outcomes in multiple spatio-temporal scales. Although this type of urban modelling has just begun, increasing numbers of researchers stress the role of complex system models in the study of land use change systems.

Complex systems models emphasise the heterogeneity of individual units in the systems and the dynamic process of interaction among those units. Complex systems are usually open systems which interact with their environments and do not seek an equilibrium state. In addition, the systems are subject to path dependency. System behaviour is a matter of initial conditions and interim variations, and the system may have various outcome states. It may be odd from a conventional urban modelling perspective, but analogy with this complex system opens a new way of understanding the relationship between individual actors and the whole society. Moreover, it also provides a new perspective on urban systems, capturing the uncertainty and non-linearity and revealing the undiscovered nature of urban systems.

Batty and Torrens (2005) argure that complex modelling differs from traditional modelling style in several ways. While parsimony and validation are two key principles in conventional urban modelling, such principles are extremely difficult or virtually impossible to apply in the case of complex modelling. Thus while traditional urban models pay attention to finding simplified causes and to validating model outcomes against empirical data, complex models pay more attention to exploring multiple causes and evaluating model outcomes in a qualitative manner. Due to the difficulty of operationalising, complex models are often expressed as storytelling helping to show different alternative states and to build consensus among participants (Briassoulis, 2008; Couclelis, 2005; Guhathakurta, 2002). In fact, Tobler (1979), who firstly introduced the notion of cellular automata models into the study of geography, also stressed the pedagogic value of such type of models.

Another concern should also be examined before applying complex science to the study of social systems. The analogy with complex systems may raise an issue of whether the study of complex system is properly applicable to the study of human society. It is very true that the social sciences have long been borrowing ideas and methods from the natural sciences. Application of Newton's gravity law for the study of land-use transportation system is only one example. At an aggregate level, such analogies with natural world mechanisms have long been accepted although there have been some criticisms about the validity of this approach for the study of social systems. In the case of a disaggregate level, on the other hand, the analogy with natural systems generates more distinctions than similarities. Because the complex system model tries to capture individual human behaviour and then to aggregate to larger society, it inevitably brings about a discussion of the nature of human beings and human society. Complexata systems by their nature do not assume institutional influences in the system. It is not difficult to find self-organising systems in the natural world, but human society is seldom constructed in an institutional vacuum. Although it can be useful not to consider institutional influences at certain micro scales or for certain purposes, it is not always logical to introduce the pure notion of complex into human social systems. Assumptions about the agents and complex systems reveal some limitations in this matter.

Regardless of such limitations, implications from complex science go beyond methodological application and call for new approaches to urban planning policy. Complex science provides a new perspective on the relationship of the society and individual actors.

Byrne (2003) argues that complex thinking is relevant to planning thinking and decision making in that it can provide a frame to work with multiple possible futures and to establish social actions that will produce a desired future. The author claims that it is not just a modelling tool but a larger framework for informing us about possible futures. Considering the fact that planning has always been shaped by various theories and methodologies of related fields, it is inferred that a newly emerging complex science and thinking can bring valuable insights into the planning field.

Planning deals with social norms and goals at a collective macro level, but it has very limited practical resources to attain desired goals especially in democratic and plural societies. Rather it often relies on direct and indirect regulations like development control and zoning systems for land use planning. What is actually taking place is not elaborated and dedicated actions by planning bodies but individuals' actions affected by those planning goals and regulations. Contemporary planning has had interests in reaching global consensus among autonomous stakeholders and participants and making collective goals and social actions, but little attention has been paid to how social members and actors react to planning policy and lead to change. Complex thinking holds some answers. Planning is fundamentally a purposeful intervention in the society at large. But, apart from such public intervention, what actually drives the changes in space is less studied in the planning field. Complex thinking can provide us with insights into how individual members actually shape the urban systems with or without planning.

Chapter 4: The Study Area: Seoul Metropolitan Area (SMA), Korea

4.1. Background

Introduction and Brief History

The study area of this research is the SMA, the capital region of Korea. Although the area is composed of a number of independent local governments, the area as a whole is often treated as one spatial unit when it comes to the growth management of Seoul and its environs. Since the SMA is the most heavily populated region in Korea, the present and future of the area often become of national interest. Having urban problems and remedies ahead of most other areas in Korea, its urban policy often sets a useful standard for other metropolitan areas in Korea. Urban modelling practice for the SMA in this sense provides implications not only for spatial policy of the SMA but also for urban policy of many other city regions in Korea. The characteristics of the study area are as follows.

Seoul is a long standing historic city but the city has experienced drastic socio-economic and spatial changes during the last century. Seoul, which is located roughly in the centre of the Korean peninsula, became the capital of Chosun Dynasty in the 14th century. Although the city was the political and economic centre of the kingdom for over 600 years, it was a pre-industrial city until the nation opened its door to foreign countries in the late 19th and early 20th centuries. Its modern urban structure such as new arterial roads began to form in the early 20th century, but the city was devastated by the Korean War in the 1950’s. The war has divided the nation into two: South Korea and North Korea, one based on capitalism and the other on communism. Seoul has remained as the capital of South Korea, and its new growth era began in the 1960’s along with the nation’s modern economic development endeavour. Seoul has been a top urban centre in the nation thereafter. Seoul has transformed itself into a post industrial city from a historic city and is now home to more than 11 million people encompassing about 605 km^2. However, Seoul no longer stands alone. The physical boundary of Seoul is fixed but its functional boundary is fuzzy and much larger. The growth of Seoul during the past decades has resulted in the formation of the Seoul Metropolitan Area (SMA) which consists of Seoul itself and other surrounding municipalities. The SMA contains about a half of the total population of Korea while it covers about 12 percent of the national territory.

Industrialisation and the Formation of the Metropolis

Although Seoul has been a capital city of Korea for several hundred years, Seoul's modern urban growth began in the 1960's along with the national industrialisation process. Its surrounding areas were predominantly agricultural areas before Seoul's abrupt urban expansion started in the 1960's. The formation of the SMA started as a result of the industrial development and economic agglomeration around Seoul city. Under the series of national economic development plans, the Korean government strategically promoted light industry around the capital region in the 1960's. Under the developmental dictatorship of the President Park Chung-Hee, the nation pursued an export-oriented industrialisation to escape from poverty and to achieve rapid economic growth. With no significant natural resources and advanced technologies available, the economic development strategy at that time was centred on labour intensive light industries which are sustained by an abundant labour force with low wages. The vicinities of Seoul city were the appropriate places to promote such labour intensive industrial development. Urban growth was the intended option to house both industry and labour. To this end, new industrial developments were intentionally placed around Seoul where the cheap labour force was abundant. Such industrial development eventually stimulated rural-urban migration, and it soon caused urban concentration in Seoul. Since then, various forms of urban development and growth have taken place in the SMA region. But, in the early stage of such industrialisation, it was only Seoul city which led to rapid urban growth in the whole SMA region, and at that time the main urban growth force in the region was agglomeration around Seoul city.

It is roughly one decade during which the Korean government purposefully promoted labour intensive light industry around the capital city region. However, the government changed the focus of the national industrialisation to heavier industry such as automobile and ship building and placed relevant industrial belts in the south-eastern part of the nation in the 1970's. Then the government promoted technology oriented industry such as electronics and further distributed industrial clusters into other rural parts of the nation in the 1980's. Despite the large degree of success of all such industries and the resulting existence of diverse regional growth poles throughout the nation, urban concentration around Seoul city and in the SMA has never ceased. Various suburban developments and sprawl effects occurred soon after, and then the region has been further shaped by post-industrial suburbanisation and urban sprawl.

In order to stop excessive expansion of Seoul, the Korean government introduced various policy measures including the introduction of a greenbelt. The government firstly improved transportation networks to existing cities outside Seoul such as Incheon and Suwon and then the government more directly triggered the metropolitanisation of the region by building large scale new towns in the late 1980's and early 1990's. Five new towns[12] which aimed at the provision of 1 million new homes were constructed outside of the greenbelt around Seoul city. These new towns were primarily residential development without much consideration of economic self-sustainment. Combined with such large scale new town developments, the development continued outside of the greenbelt, causing the rise of many other cities and forming a big metropolitan area.

[12] Bundang, Ilsan, Pyeongchon, Sanbon, and Joongdong

Now urban growth takes place throughout the whole SMA, but the SMA is not a large conglomeration of pure urban regions. In fact, the entire region encompasses a large number of non-urban and functionally less homogeneous areas, but the SMA is considered as a single metropolitan area for practical urban policy purposes in Korea.

4.2. Characteristics of the Area

Geography and Topography

The area of the SMA in 2010 is approximately 11,801 km^2, 11.8% of the total area of Korea, but containing about half of the total population of Korea (which was 49 million in 2010)[13]. This is a large dispersed metropolitan area which is more or less comparable with the Greater South East in the UK. The study area as a grid space is approximately 132 km wide and 155 km long. It is located in the north western part of the nation, and the area borders North Korea to the north. The Demilitarised Zone (DMZ) was installed as a buffer zone in the area between South and North Korea after the Korean War, and the area outside the DMZ, which is the northern edge of the SMA, is heavily militarised. To the east, the SMA borders the province Kangwon which is the most mountainous area of Korea. Thus the eastern part of the study area is dominated by a high-altitude area. On the west, it borders the West Sea which is an area containing flat plains and low rising hills. The southern part of the area also has relatively flat areas and it borders Chungcheong province. The Han River which is the main water source of the region flows from east to west in the middle of the region and through the city. Two upper rivers, the North and South Han River, merge outside of Seoul, and the river passes through the middle of Seoul city. The environs of Seoul city are protected by a greenbelt. The key

[13] Source: Ministry of Land, Transport and Maritime Affairs. Statistical Yearbook of MLTM (2009).

geographic features and overall topographical characteristics of the study area are depicted in Figure 4.1.

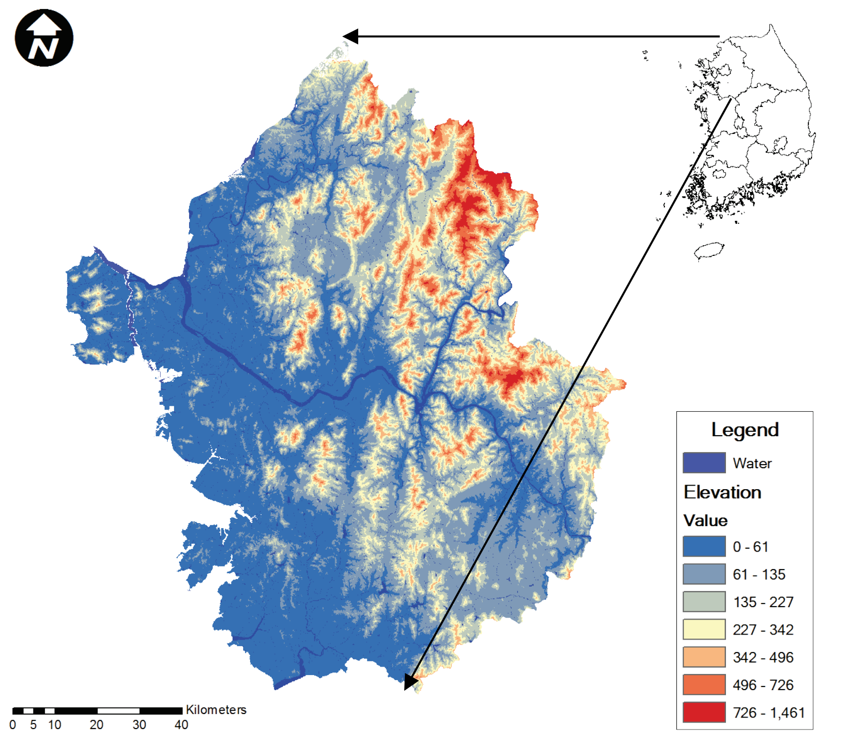


Figure 4.1. Topography of the Study Area

Municipalities

Currently the SMA consists of Seoul city which is the functional and physical core of the region and 32 surrounding municipalities[14]. All 33 cities have a varying level of population size. Among the 33 municipalities, Seoul city itself and some several surrounding cities are heavily populated. Seoul city has the biggest population of some 10,000,000. Incheon and

[14] The Seoul Metropolitan Area is a term describing the area under the socio economic influence of Seoul and is not a unit of local government. The area consists of 3 local governments at a top tier: the City of Seoul, the City of Incheon, and the Province of Kyunggi. Although each of the three has sub level local governments, Seoul and Incheon are counted as single cities here, and the number is combined with all other 31 municipalities in Kyunggi province.

Suwon have populations of more than 1,000,000, and seven out of the total 33 municipalities have more than 500,000 populations. In contrast, some municipalities such as Yeoncheon-gun, Gapyeong-gun, and Yangpyeong-gun are less affected by urban growth and have a population under 100,000 regardless of their large areas. The existence of various levels of local government is essential for delivering necessary public services, but the effective growth control would be impossible at the level of a single administrative body due to various spatial externalities. For this reason, the SMA is often treated like one whole region for a number of urban policies by the national government. See Figure 4.2 and Table 4.1 for the spatial distribution of population in the SMA.

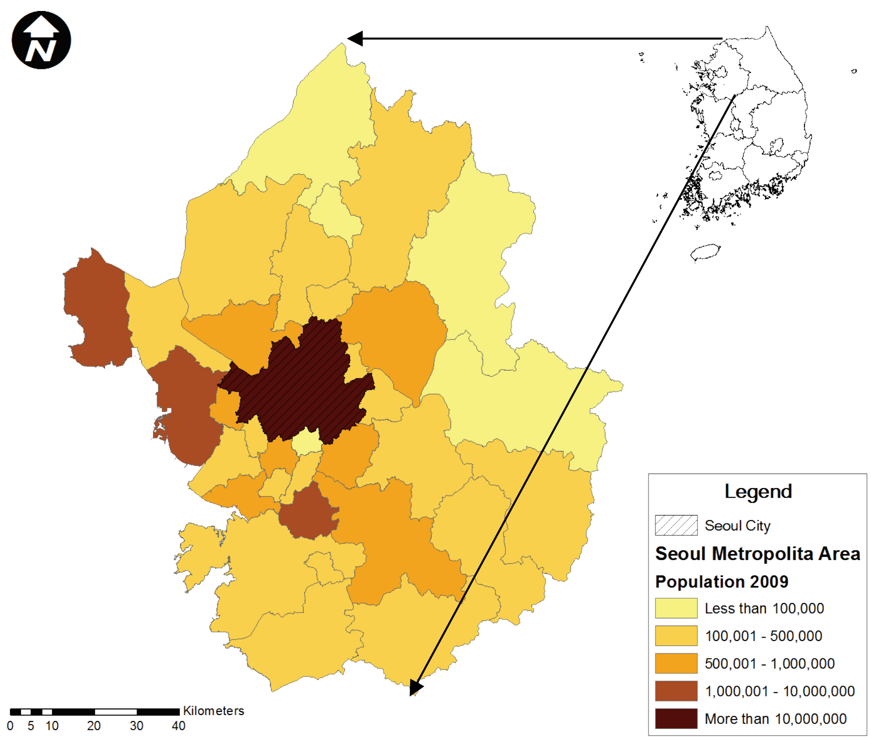


Figure 4.2. Municipalities in the SMA

Note: The SMA has dozens of small islands in its western parts where it is bounded by the West Sea. However, those islands are not included in this map.

Table 4.1. Population Distribution of the SMA in 2009

	Area (㎢)	**Population**
Total	11,801.23	24,379,491
Seoul	605.28	10,208,302
Incheon	1,010.35	2,710,579
Suwon-si	121.01	1,073,149
Seongnam-si	141.72	962,726
Uijeongbu-si	81.54	431,008
Anyang-si	58.46	616,547
Bucheon-si	53.44	869,944
Gwangmyeong-si	38.50	314,257
Pyeongtaek-si	454.63	410,042
Dongducheon-si	95.66	93,211
Ansan-si	148.48	705,346
Goyang-si	267.41	938,784
Gwacheon-si	35.86	72,049
Guri-si	33.30	195,593
Namyangju-si	458.53	525,211
Osan-si	42.77	159,734
Siheung-si	134.57	397,912
Gunpo-si	36.36	140,874
Uiwang-si	54.01	275,731
Hanam-si	93.04	148,566
Yongin-si	591.32	839,204
Paju-si	672.47	323,011
Icheon-si	461.28	197,496
Anseong-si	553.51	170,919
Gimpo-si	276.60	225,805
Hwaseong-si	688.28	491,528
Gwangju-si	430.96	238,583
Yangju-si	310.21	182,106
Pocheon-si	826.48	158,931
Yeoju-gun	607.72	108,088
Yeoncheon-gun	696.19	45,241
Gapyeong-gun	843.48	57,564
Yangpyeong-gun	877.81	91,450

Source: Statistics Korea, accessed 23/12/2011, http://www.kosis.kr/abroad/abroad_01List.jsp

Population Growth Trends

Rapid population growth of the SMA has started along with the population growth of Seoul. The city of Seoul experienced explosive population growth during the 1960s and 1970s. About 2.5 million people lived in Seoul in the year 1960, which was around 10% of the national population. However, the population of Seoul city has increased to 8.3 million by 1980, and the city contained around 22% of the total national population in 1980[15]. This can be attributed to the sharp increase of in-migration into Seoul during those periods. However, due to the government's regulation of new development and the lack of available land, the rate of population growth in Seoul city began to slow down from the 1980's. Then, the suburbanisation process became prominent from the 1980's causing urban growth in the various parts of the SMA.

As a result, the SMA as a whole has continuously experienced dramatic population growth over the past decades. The region has been the centre of various high profile socio-economic and cultural activities in Korea – politics, finance, commerce, higher education, research and development, media, and entertainment. Such functional agglomeration once again has attracted population from elsewhere in Korea and from abroad. As a result, the population has almost doubled over the past two decades. Total population of the region was 15,803,288 in the year 1985 but it was 24,379, 491 as of 2009. This large population growth vividly shows the rapid urban growth taking place in the area. Although the population growth rate of the SMA has slowed since 2000, the region is still gaining population. The SMA's population increased from 22.0 million in 2000 to 24.3 million in 2009, which is 49% of the total population of Korea. If this trend continues, the population of the SMA will continue to grow, and according to the figures projected by the National Statistical Organisation of Korea, total population of the SMA will reach 25.7 million by 2020 and 26.3 million by 2030 when it is projected that more than 54%

[15] Source: Statistics Korea (http://www.kosis.kr)

of Korea's population will live within the SMA. Table 4.2 summarises the past population growth trends of the SMA. Table 4.3 shows the projected population growth.

Table 4.2. Past Population Growth

	1985	**1990**	**1995**	**2000**	**2005**	**2009**
Whole country	40,419,652	43,390,374	44,553,710	45,985,289	47,041,434	49,773,145
SMA	15,803,288 (39.1%)	18,573,937 (42.8%)	20,159,295 (45.2%)	21,258,062 (46.2%)	22,621,232 (48.1%)	24,379,491 (49.0%)

Source: Statistics Korea, accessed 23/12/2011, http://www.kosis.kr/abroad/abroad_01List.jsp

Table 4.3. Projected Population Growth

	2010	**2015**	**2020**	**2025**	**2030**
Whole country	48,874,539	49,277,094	49,325,689	49,107,949	48,634,571
SMA	24,336,199 (49.8%)	25,191,245 (51.1%)	25,786,378 (52.3%)	26,161,866 (53.3%)	26,315,824 (54.1%)

Source: Statistics Korea, accessed 23/12/2011, http://www.kosis.kr/abroad/abroad_01List.jsp

4.3. Scenarios for Urban Growth Simulation

Business as Usual

The SMA has experienced diverse growth within relatively a short time period although the growth of the SMA is largely shaped by the influence of Seoul city. Urban growth in the SMA was centred on Seoul city until the 1970’s. However, after the introduction of the greenbelt in the early 1970’s, the physical expansion of Seoul city has been strictly regulated.

While the greenbelt has successfully prevented further expansion of Seoul, it could not reduce the need for urban development itself, and as a result, new urban development has occurred in various locations outside the greenbelt in the SMA, thus leapfrogging along the constrained area which is reminiscent of growth patterns in many other large cities such as London which have a long history of containment through greenbelt policies.

Intensive population influx and increases in the SMA is one of the main reasons which has caused the dramatic conversion of open space into urban built up areas. The historic urban extent clipped from land cover data by the Korean Ministry of Environment catches rather well the past urban growth trend of the SMA. Land cover change maps below, drawn from 30m×30m Thematic Mapper (TM) Satellite Images, show such urban development patterns between 1985 and 2006.

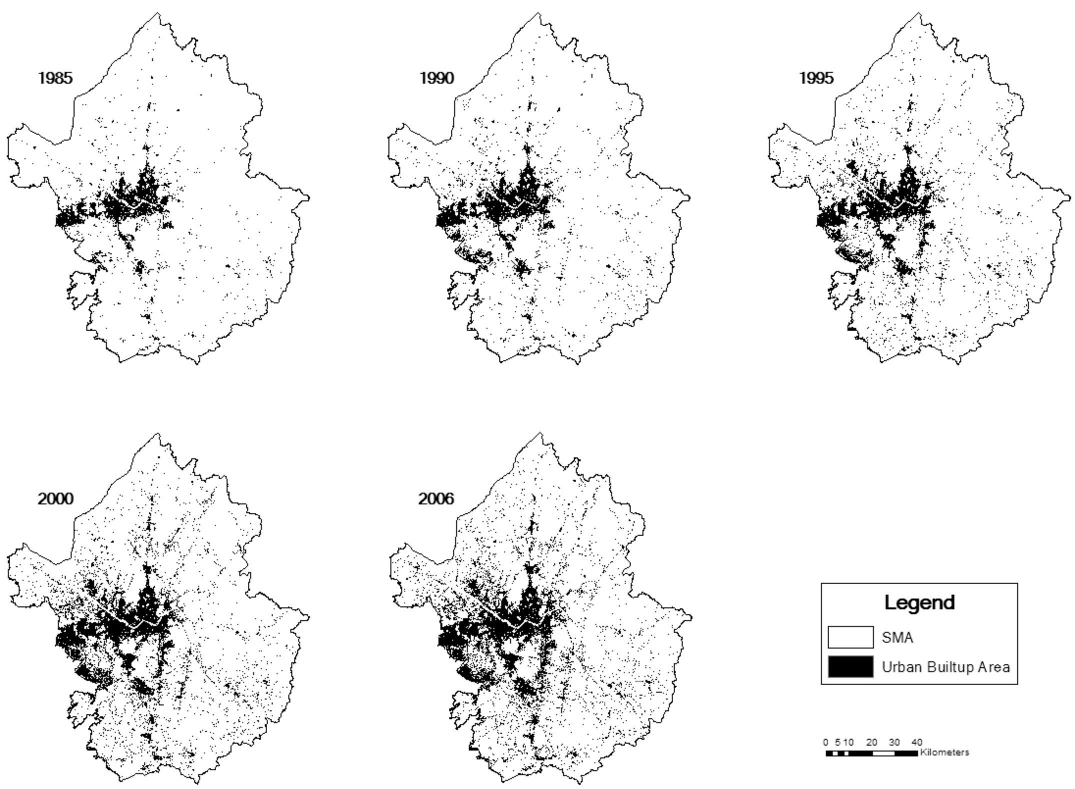


Figure 4.3. Changes in the Urban Built-up Area in SMA, 1985-2006

It is clear that the total urban built-up area of the SMA has significantly increased over time. The data show that the urban built-up area increased from approximately 5.7 percent of the total land area in 1985 to 15.2 percent in 2006. The increase has slowed during the 2000's, along with a slowing population growth rate of the SMA. However, the urban built-up area in the SMA has continuously increased, consuming available open space and damaging the natural environment. In addition, scattered urban development is much more notable than 10 years ago. The overall urban growth pattern and the changing form of the study area are depicted in Figure 4.3.

Two types of urban development have shaped the overall urban growth of the SMA. Firstly, the public sector has led to large scale development in the SMA. In an effort to resolve the housing shortage problem in the capital city Seoul, a series of major new town developments took place in the 1990's in areas close to Seoul such as Bundang, Ilsan, and Pyeongchon. More new town development but at a much smaller scale has occurred more or less continuously at further distances due to the depletion of large scale vacant sites near Seoul. Secondly, small scale development by private developers has followed these larger developments, eventually resulting in a serious urban sprawl problem in the SMA. As a result, the SMA has suffered greatly from urban sprawl over the last decade. Necessary policy measures have been taken to stop undesired urban sprawl, but the small scale and dispersed development pattern dominates current urban growth in the SMA[16].

Current urban developments occurring in the study area are small scale and virtually out of planning control. Since planning in South Korea adopts zoning systems for land use planning, there are no particular measures to control those individual developments if these are not

[16] The sprawling urban growth pattern was identified by conducting a patch analysis of land cover data for 2001 and 2009. Whereas the number of urban patches has increased from 10472 to 22900, average patch size has decreased from 13.41 to 6.44 hectares. The result implies that the urban built-up area has increased but at a much smaller scale and higher urban density.

violating zoning regulations and some environmental assessments. In nature, those developments are individual, autonomous, and heterogeneous – the system is self-organising and complex. Understanding the dynamics of current status and forecasting future growth patterns are necessary tasks for the region's sustainable future.

Figure 4.4 and Table 4.4 show land cover distribution of the SMA in 2009 and summarises the current spatial arrangement of the SMA. Among total land uses in the SMA, the majority, 48.9 percent of the study area, is covered by forest. The high proportion of forest land is due to the topographical characteristics of Korea. Mountainous terrain covers about two-thirds of the whole nation. Such terrain usually has low suitability for urban development due to steep slope conditions and acts as a natural barrier to urban growth. Agricultural land, which has long been vulnerable to urban development, accounted for 24.2 percent. The study area contained approximately 13.0 percent of the urban built-up area in 2009.

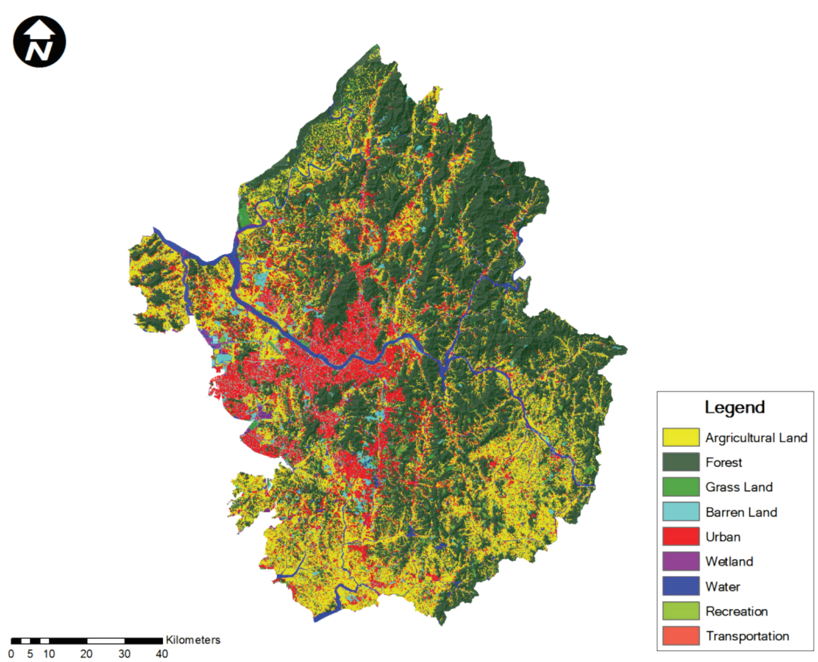


Figure 4.4. Land Use of the SMA, 2009

Table 4.4. Land Cover Distribution 2009

	Cell count	Area (km^2)	Percent
Agricultural Land	1102237	2755.6	24.2
Forest	2227481	5568.7	48.9
Grass Land	144449	361.1	3.2
Barren Land	140806	352.0	3.1
Urban	590275	1475.7	13.0
Wetland	50208	125.5	1.1
Water	149980	375.0	3.3
Recreation	18907	47.3	0.4
Transportation	126491	316.2	2.8

Note: The original land cover data was rasterised to a cell size of 50m x 50m. The area was calculated from the cell count. It also shows the initial spatial arrangement for future simulations.

It is foreseeable that future growth will further consume vulnerable agricultural areas. Certain areas such as the south west part of the SMA were relatively underdeveloped rural areas until around year 2000. But after then, considerable development has begun to occur and now it is one of the fastest urbanising areas in Korea. The main factor causing such urbanisation is housing development, caused partly by the leapfrogging effect. Seoul, a city surrounded by a wide greenbelt, cannot hold the continuing demand for land. The greenbelt around Seoul has blocked the physical expansion of Seoul, but developments simply take place outside the greenbelt, along with a good transportation network. Nearby areas outside the greenbelt have sequentially urbanised from the decades ago, and this is spreading to outer parts of the SMA. Thus, urban development in the SMA occurs wherever possible, but the urban development of the SMA is generally conditioned by the following sub-regional characteristics. The northern part is generally dominated by mountainous terrain which decreases the possibility of urban development. The eastern part is largely protected by environmental regulations because the Han River, the water source of Seoul, runs towards west from east. Less transportation infrastructure is established in that region. The western part is a densely industrialised area and has little room for new deployments. The southern part of the SMA holds a relatively large amount of agricultural land and provides good access to Seoul along with a well-established transportation network. The urban growth of the region has generally reflected these conditions.

Deregulation of Greenbelts

The greenbelt of the SMA was firstly designated around Seoul city in 1971 and around a dozen other municipalities in the following years. The greenbelt was viewed as a most effective means to control the rapid expansion of Seoul. Accordingly most urban development has been strictly prohibited within the designated greenbelt areas. As of 2009, the SMA's greenbelt covered 1,540.8 km^2 which is about 13.1 percent of the total area of the SMA[17].

The Korean government[18] has taken a very conservative position on greenbelt policy. The physical boundary of the SMA's greenbelt has remained virtually unchanged for three decades. However, the SMA is the economic centre and the most heavily populated area of the nation. Strong land demand for urban and suburban development will never vanish. Not surprisingly there has been a steady demand for adjusting the greenbelt boundaries to

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[17] Source: Ministry of Land, Transport and Maritime Affairs. 2020 Master Plan for Seoul Metropolitan Area (2009).

[18] Greenbelts are formally known as Restricted Development Zones in the planning legislation of Korea. After a couple of changes, currently it is prescribed in the Law of National Land Planning and Use. According to the law, the Ministry of Construction (the predecessor of the Ministry of Land, Transport and Maritime Affairs) delineates and maintains the boundaries of greenbelts.

accommodate more urban development. In this regard a marginal release of the greenbelt has been sought from the early 2000's although it has been a political decision of the former government. Deciding the location and quantity of this release has been an important planning debate for many years, but this is not fully elaborated in this study.

After intensive research and public consultation, the government specified the possible release of greenbelt land in the SMA's metropolitan plan. It was decided that a total area of 125.8 km^2 in the SMA would be gradually released to accommodate new development. Various public development projects such as the industrial complex and public housing are being considered by national and local governments on those areas. Figure 4.5 shows the location and shape of the greenbelts around Seoul, and Table 4.5 elaborates the future release of the greenbelt.

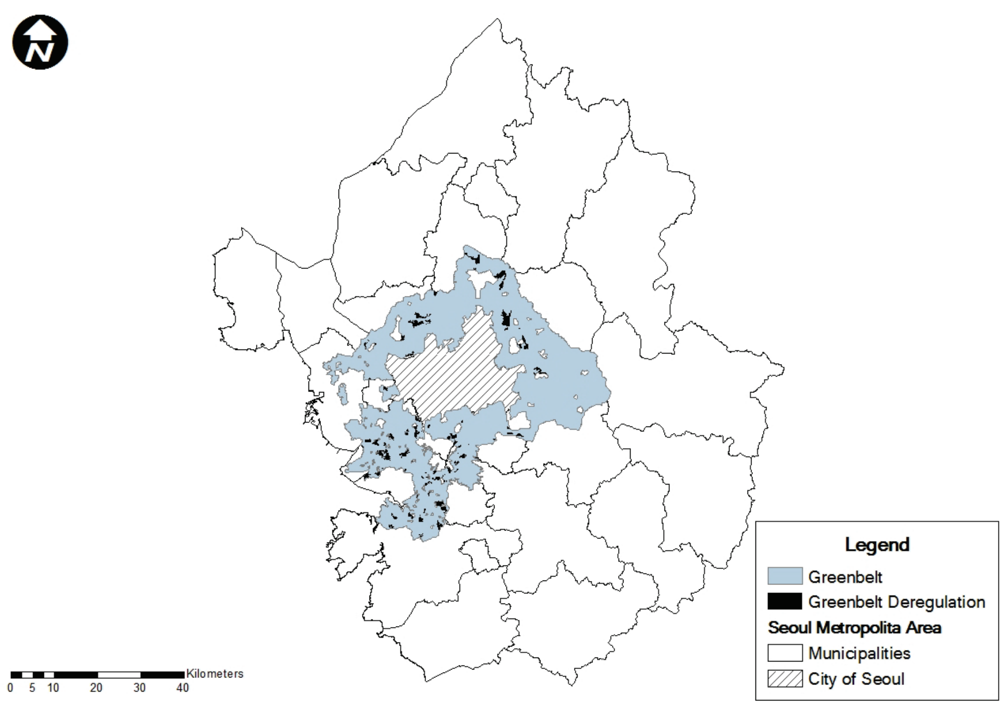

Figure 4.5. Map of Greenbelt and Location of Proposed Deregulation

Table 4.5. Current Containment and Possible Release of Greenbelt by Municipalities

	Current Containment (km^2)	Possible Release	
		Area (km^2)	Percent (%)
Total	1,540.8	125.8	8.16
Seoul	166.8	13.3	7.98
Incheon	80.6	8.3	10.28
Goyang	134.4	13.1	9.71
Gwacheon-si	33.0	2.5	7.60
Gwangmyeong-si	29.8	3.3	11.23
Gwangju-si	106.5	7.0	6.53
Guri-si	23.4	1.9	8.02
Gunpo-si	24.7	2.5	10.15
Gimpo-si	18.8	1.5	8.06
Namyangju-si	241.9	11.3	4.67
Bucheon-si	20.4	2.1	10.33
Seongnam-si	54.8	5.3	9.59
Suwon-si	36.5	3.0	8.10
Siheung-si	102.5	12.1	11.78
Ansan-si	39.6	4.5	11.47
Anyang-si	31.0	2.6	8.43
Yangju-si	79.0	4.5	5.65
Yangpyeong-gun	17.2	1.1	6.16
Yongin-si	3.6	0.2	6.03
Uiwang-si	49.8	5.1	10.21
Uijeongbu-si	63.9	5.9	9.20
Hanam-si	86.4	7.1	8.16
Hwaseong-si	96.2	7.6	7.86

Source: Ministry of Land, Transport and Maritime Affairs. 2020 Master Plan for Seoul Metropolitan Area (2009)

Construction of GTX

The Korean government is planning to build a new high speed rail network, GTX (Great Train eXpress), which has a maximum speed of 160~200km/h and an average speed of 100km/h, in the SMA. It is expected that the project will be completed by 2016, and once operational, the new system will provide efficient transportation between major business districts in Seoul city and other cities in the SMA. The fundamental purpose of the introduction of such a high speed railway system is to accommodate increased traffic demands and mitigate chronic traffic congestion problems in the SMA. The GTX planning body estimates daily users of 0.76 million by 2016. Estimated benefits include a decrease of 0.88 million cars on the road per day, an annual CO^2 emission reduction of 1.5 million tons, and the creation of 0.26 million jobs (Gyeonggi-do, 2009).

Figure 4.6 and Table 4.6 show the planned routes and stations in relation to various municipalities in the SMA. The planned routes consist of three lines and twenty two stations. According to the proposal made by Gyeonggi-do[19], Line A connects KINTEX[20] and Dongtan with a length of 74.8km; Line B connects Songdo and Cheongnyangni with a length of 49.9km; and Line C connects Uijeongbu and Geumjeong with a length of 49.3km. Since the GTX aims to facilitate commuting to/from the major business districts in Seoul city, half of the proposed stations are located in the City of Seoul. The rest are located in major residential areas and strategic traffic nodes outside Seoul city.

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[19] The GTX project was originally proposed by Gyeonggi-do, the provincial government comprising all municipalities except Seoul and Incheon in the SMA, in 2009. Then the Ministry of Land, Transport and Maritime Affairs commissioned a feasibility study and decided to introduce the GTX in the SMA. However, the location of routes and stations are not yet finally confirmed by the national government at the time of this study. This research uses the original routes and stations proposed by Gyeonggi-do.

[20] KINTEX (Korea INternaTional EXhibition centre) is an exhibition centre located in Ilsan-gu, Goyang-si, Korea.

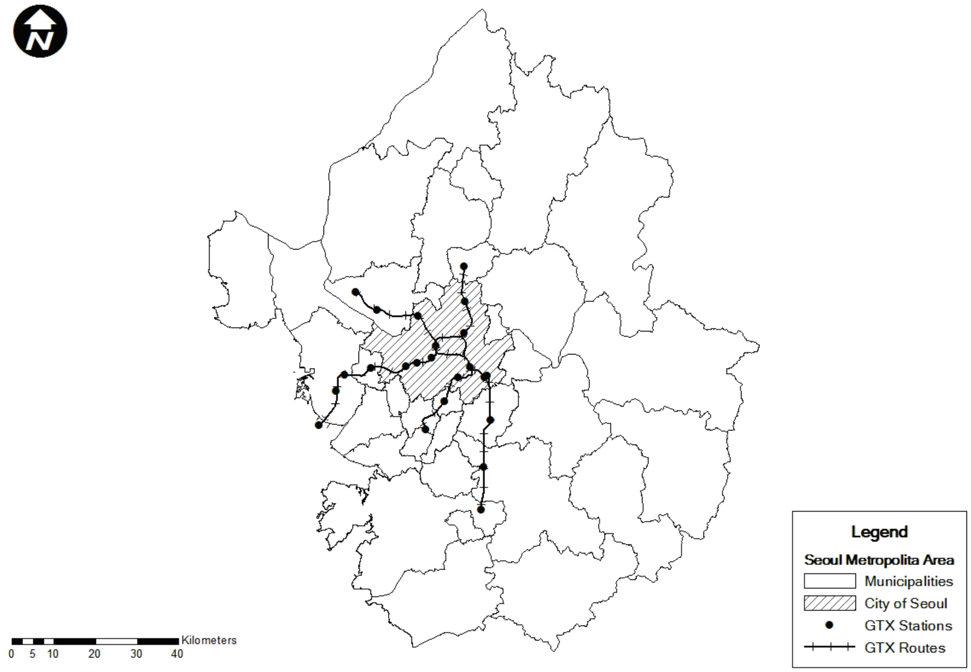


Figure 4.6. Proposed GTX Routes and Stations

Table 4.6. Proposed GTX Routes and Stations

	Line A	Line B	Line C
Stations	KINTEX, Daegok, Yeonsinnae, Sinchon, Yongsan, Express Bus Terminal, Samsung Pangyo, Giheung, Dongtan	Songdo, Incheon City Hall, Bupyeong, Dangarae, Sindorim, Yeoui-do, Yongsan, Seoul Station, Cheongnyangni	Uijeongbu, Changdong, Cheongnyangni, Samsung, Yangjae, Gwacheon, Geumjung
Length	74.8km	49.9km	49.3km

Source: Gyeonggi-do (2009)

Although the main benefit would be a better transportation system in the SMA, it is evident that this first high speed rail system in the SMA will significantly affect the future urban growth pattern in the region by changing the mobility between areas and reducing the reliance on road traffic. The role of transportation and accessibility on urban growth is indeed well perceived in orthodox urban economic theories (Alonso, 1964; Anas, 1978; Fujita, 1986). It is also known that the high speed transportation system results in urban expansion, and the transportation nodes become nuclei for urban growth, promoting polycentric spatial structure (Debrezion, Pels, and Rietveld, 2007). Proximity to transit stations provides reduced travel time and cost, and eventually it promotes local agglomeration of urban activities.

Overall Urban Development Trends and Prospects

As seen earlier, the SMA has experienced rapid urbanisation over the past decades. Although urban concentration has been a necessity for the promotion of labour intensive light industry, the government soon realised the urban problems resulting from excessive growth of Seoul and tried to stop the expansion of Seoul city. To this end, the Korean government introduced the greenbelt policy in 1971 to stop the physical expansion of Seoul. The greenbelt around Seoul has been strictly preserved, and it is considered as a main constraint of the physical expansion of the Seoul city. However, the result is leapfrogging development just outside of the greenbelt area. The growth of Seoul has stopped but the SMA as a whole is continuously consuming available land and damaging the natural environment.

In the past, large scale urban development by public sectors to accommodate housing needs has characterised overall urban growth in the SMA. However, with a slowing population growth as well as the depletion of large scale vacant land, such development practice is no longer a dominant force of urban growth in the SMA. Instead small scale bottom-up urban development characterises recent urban development in the region.

This rapid urban growth and sprawl in the SMA has resulted in diverse urban problems such as raised infrastructure costs and damaged natural environments. It is foreseeable that future growth would further consume vulnerable agricultural areas. Urban development in the

SMA occurs wherever it is possible. However, in a democratic market regime, there are no absolute means to prohibit such spontaneous urban development. It is thus particularly important to understand how complex urban growth occurs and how certain policy actions can intervene to reduce the problems of growth and sprawl. We thus move on to examine what urban growth models might be able to tell us about urban growth in Seoul, and we begin with the SLEUTH model.

Chapter 5: Experimental Simulation 1: The SLEUTH Model

5.1. Background of Simulation

SLEUTH, an urban growth and land use change simulation model, was originally developed by Keith Clark at the University of California, Santa Barbara, in the early 1990s under the auspices of the US Geological Survey (USGS) and Environmental Protection Agency (EPA). The model has two independent subcomponents: to simulate urban growth dynamics (UGM) and land use change dynamics (Deltatron). However, the latter has been less widely used than the former and the UGM often represents the SLEUTH model. The model was initially applied to the San Francisco Bay area from 1993-1997 (Clarke et al., 1997) and since then the model has been applied to over 100 cities and urban regions around the world (Clarke, 2008). The model has provided useful understanding of urban growth and its implications for planning policies in diverse regions and it is clearly one of the most widely used cellular automata based urban growth simulation models which focuses on urban growth and development. It is worth noting however that this class of model is based on very different sets of assumptions from the other main class of LUTI models that focuses much more on activity location and spatial interaction rather than the actual physical development and land use that is the focus of these cellular automata type models.

SLEUTH is a non-proprietary generic model. Generic urban models are pre-packed and ready to use for a wide variety of study areas without further development or modification although SLEUTH itself is an open source model which provides the possibility of further customisation. A key to the use of a generic urban model for a desired study area is model calibration. In general model calibration is a process of adjusting model parameters in order to make the model behave correctly or in a tolerable manner. However, the calibration of SLEUTH mainly involves two distinctive research efforts. Firstly, calibration of SLEUTH is not simply to determine model parameters but to make the model behave suitably for a given study area. Here the main aim is to adapt the model to the local characteristics of the study area and to examine whether or not it well represents the unique geographic settings of the area (Silva and Clarke, 2002, 2005). Then the model is run for the future to study future change in the area. Secondly, since the SLEUTH has a unique semi-automatic calibration process supported by ranges of statistical analyses and metrics to adapt itself to a specific study area, an optimisation of such a method is also an important research focus with regard to the calibration of the SLEUTH model (Dietzel and Clarke, 2007; Jantz et al., 2010). Here the calibration of SLEUTH involves the investigation of better means to determine model parameters.

The main purpose of this chapter is a calibration of the SLEUTH model, but this study is not about a successful calibration but about lessons learned from an unsatisfactory calibration and simulation of SLEUTH. The aim of the calibration in this sense falls into neither case mentioned above. This research applies SLEUTH to a case study area, the SMA, in Korea. However, it does not attempt to study future growth of the area through the adaptation of the model to the given local characteristics and the production of rigorous model outcomes. Although the model has such a capacity, it has been limited by the inadequacy of input data for this study. Instead an ultimate aim here is to gain a better understanding of cellular automata based urban models through an experimental simulation with SLEUTH. It is rather an empirical review of one of the leading cellular automata based urban models on the way to developing a dedicated agent based model which will be introduced in the latter part of this thesis.

In doing this, particular attention is given to the data oriented calibration method of SLEUTH. The calibration of SLEUTH is data oriented in that it derives model parameters from data. Estimation of model parameters from empirical data is in fact not unusual for scientific models. However, its unique extraction methods and issues inherited from the use of raster based geospatial data are well worth discussing.

To achieve all the goals, this study explores the fundamentals of SLEUTH and then conducts the calibration and simulation for the study area. Lessons and implications from a broader view of complex modelling will be discussed at the end of this chapter.

5.2. Model Description

Data Requirements

The model name is an acronym of six types of spatial data layer: **S**lope, **L**and use, **E**xclusion, **U**rban, **T**ransportation, and **H**illshade. Except for the hillshade layer, which is optionally used as a backdrop image for visualisation purposes, all of the other five layers are essential for model calibration and future simulation. The model requires greyscale 8 bit GIF images as an input data format which have a pixel (cell) value from 0 to 255. Relevant cell values for each layer are assigned in this range. All input images must be spatially consistent. They must have the same spatial resolution (size of individual cell) and spatial extent (size of entire cell space) so that the cells in all layers can be properly aligned. Since SLEUTH is a pure model without data processing capability as part of its core software, such input data need to be prepared with external GIS and image processing software. The roles and characteristics of each layer are as follows:

- Slope is one of the most important natural conditions which affects urban development. Thus it often becomes an essential element for assessing land suitability. A commonly agreed assumption is that urban development practically does not occur above a certain degree of slope and that generally a steeper slope is less preferred due to increasing time and cost for development. The slope layer is used to define terrain conditions and physical suitability in this regard. The slope value must be in percent value rather than degree. Thus the cell values range from 0 to 100.

- Land use data are necessary for the land use change sub model Deltatron but not for the urban growth sub model UGM. Cell values are arranged between 0 and 255, each representing a unique land use classification.
- The exclusion layer defines the area not subject to future urban growth by any means. It may include natural barriers such as water bodies and/or institutional protection such as national parks. A cell value 0 is considered as freely developable land, and no development can take place in a cell with a value of 100 or above. The values between 0 and 100 can also be assigned to represent a degree of partial exclusion.
- The urban extent layer defines previously urbanised areas and becomes the basis for urban growth simulation. This urban layer holds the cells evolving over time while other layers are used as references for this transition. A zero cell value represents a non-urban state which has a potential for urban transition. Any value between 1 and 255 is read as an urban state.
- The transportation layer defines a cell's accessibility to road networks and derives the road influenced growth. SLEUTH allows road weighting so that it can consider different levels of road accessibility. A zero value implies no road, and a weighting is possible by using a value between 1 and 255.

The above are the requirements in a spatial context. The temporal requirement depends on the different modes of the model such as test, calibration, and prediction. The prediction mode is a module to simulate future growth from a single latest or desired time point of the above mentioned input layers. The calibration mode is a process for deriving model parameters to be used for the prediction model. All six (or five) layers are necessary, but multiple time periods are demanded for certain layers. The urban layer requires most intensive historic data. With at least four time periods necessary for model calibration, the earliest year is used as a seed to initiate calibration, and the other three are used for comparison with simulated results. After calibration, the latest year becomes the seed layer for the prediction mode. Two different time points are necessary for the calibration in the case of the transportation network. The test mode is a module to verify the consistency of input data to be used in the calibration and prediction. Thus it does not have an independent data requirement but it checks the validity of input data for the calibration or prediction mode.

Model Structure and Behaviour

A standard cellular automata system framework first of all forms the backbone of SLEUTH. The model adopts the core elements of cellular automata systems to simulate urban growth: 1) the cell: the basic computational unit in a cellular automata system. A cell size is defined as an input data resolution in SLEUTH; 2) cell space: a two dimensional array of cells. It is defined by the dimension of the input data; 3) cell state: An attribute value assigned to the cell. Each input layer holds relevant cell values between 0 and 255; 4) neighbourhood: the spatial relationship of one cell to another. SLEUTH uses a classic Moore neighbourhood, 8 cells based on a 3x3 grid of which the central cell is the focus of the neighbourhood, and 5) transition rules: conditions governing the change of a cell state from one to another. It is typically defined by the states of neighbouring cells in the case of simple cellular automata systems. In the case of SLEUTH, the cell transition occurs in the urban layer, but the model incorporates additional information from reference layers such as slope and transportation as well as information from model parameters.

Based on such cellular automata system fundamentals, the urban growth dynamics is jointly determined by a range of additional functions and methods in order to capture realistic urban system behaviour. Basic building blocks are 1) suitability conditions, 2) growth rules, 3) growth coefficients, and 4) self-modification rules. The suitability condition globally filters out those cells that are not subject to future growth and also defines basic potentials for urban growth. This condition is defined by two input layers: the exclusion and the slope layer. The area in the exclusion layer is literally excluded from future growth. In addition the areas with slopes greater than 21 percent are also excluded by default (note that this threshold can be modifiable). All other areas are relevant to future urban growth, but the potential for urbanisation is calculated by the slope value at each cell and the globally defined slope coefficient.

The growth rules form the core of urban growth dynamics in SLEUTH. Under the pre-defined neighbourhood, this defines how individual cells become 'urban' or remain 'non-urban' when they meet certain conditions. SLEUTH defines four types of growth rule which occur sequentially and iteratively: spontaneous growth, new spreading centres, edge growth, and road-influenced growth. A set of four growth types completes one growth cycle which represents one year in the simulation environment. These growth rules are the essence of SLEUTH and embody how the model encapsulates dynamic urban growth patterns and processes. The very strength of SLEUTH or any cellular automata system stems from these types of transition rule. A set of simple rules that only governs interaction between neighbouring cells can generate global level behaviour. Details of each growth rule are as follows.

Spontaneous growth represents the random urbanisation of land. It simulates small scale low density urban development which occurs independently from existing factors such as urban clusters and transportation networks. Any non-urbanised single cell except for certain excluded cells can be converted into an urban cell in any time step of the model running. Since the location of this urban growth transition is randomly selected, it is not affected by neighbouring cell conditions. The total number of cells to be randomly converted into an urban state is controlled by the dispersion (diffusion) coefficient.

A new spreading centre determines whether isolated single urban cells generated in the previous step will become new urban centres which have capacity for further urban expansion. Once the cell is selected as a new spreading centre, two neighbouring cells are additionally converted into urban cells forming an urban block which has three or more urban cells. The probability of a new single urban cell becoming a spreading centre is defined by the breed coefficient.

Edge growth further defines urbanisation from the established spreading centres. This type of growth simulates the expansion of existing urban clusters into their surroundings. If a non-urban cell has at least three urbanised cells in its neighbourhood, then the non-urban cell has a certain probability of becoming an urban cell. In this way, new spreading centres, existing urban clusters, spread out and enlarge their sizes. The spread coefficient controls this type of growth by defining a probability of a non-urban cell with at least three urban cells in the neighbourhood becoming an urban cell.

Road-influenced growth, as the name suggests, represents urbanisation largely directed by transportation networks and hence by accessibility. In this final growth step, growth is jointly determined by the existing transportation network and the most recent urban development generated in the previous three steps. This consists of a range of steps affected by different coefficients, but in a nutshell it ultimately generates spreading centres adjacent to the road networks, allowing urbanisation of up to two cells along the roads. The sequence is as follows. Firstly, newly urbanised cells are selected with a probability defined by the breed coefficient. Then the existence of a road is checked within a given maximum radius specified by the road-gravity coefficient. If a road exists within the radius, a temporary urban cell is placed on the road at the closest point to the selected cell. Then the temporary urban cell randomly walks along the road with the maximum distance defined by the dispersion coefficient. The final location of the temporary cell is then considered as a new urban spreading centre, and two additional neighbouring cells are converted into urban cells. The above steps are referred to as a road trip, and the number of attempted road trips in each growth cycle is defined by the breed coefficient.

As briefly mentioned, the above four growth rules are controlled by five growth coefficients: namely dispersion, breed, spread, slope, and road gravity. Each parameter has a value from 0 to 100 and guides single or multiple growth rules.

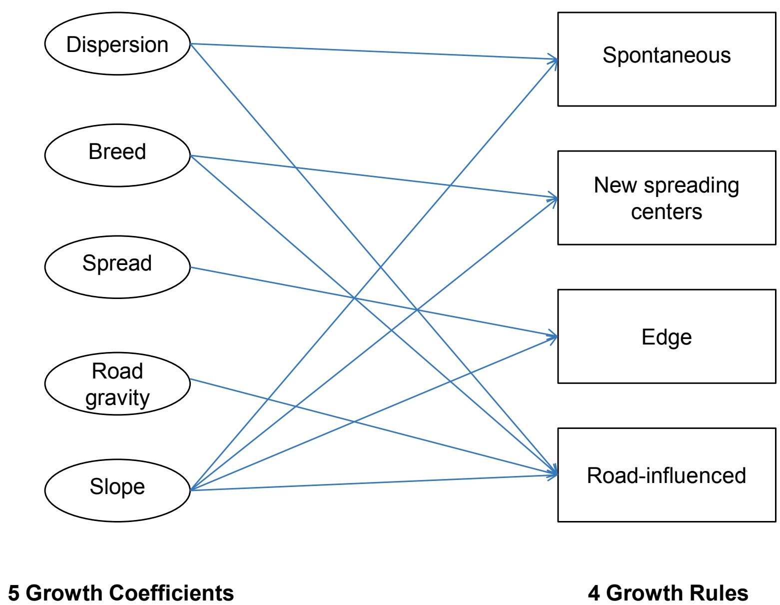


Figure 5.1. Growth Rules and Controlling Coefficients

The dispersion coefficient governs spontaneous growth by defining the total number of single cells to be selected for urbanisation. It also controls the road influenced growth by defining the random movement distance of a temporary urban cell on the road to spread new development. The breed coefficient controls new spreading centre growth and road influenced growth. It defines the probability of newly urbanised spontaneous growth cell becoming a new spreading centre. It also determines the number of road trips to be taken place in one growth cycle. The spread coefficient controls the edge growth and defines the probability of urban cells in the spreading centres generating additional urban cells in their neighbourhoods. The road-gravity coefficient determines the maximum radius to be used for searching for the existence of a road from a newly urbanised cell. The slope coefficient affects all growth rules by providing the cell probability of urbanisation. The relationship between the four growth rules and the five controlling parameters are illustrated in Figure 5.1.

In addition to the growth rules and coefficients that invoke and control urban growth shown in Figure 5.1, another rule set kicks in to complete the urban growth dynamics of SLEUTH. While the five coefficients are defined as model parameters at the beginning of the simulation, the self-modification rules at the global scale dynamically alter certain coefficients during the simulation runs. What this does is speed up or slow down overall urban growth. This self-modification feature aims to add a degree of non-linearity to the overall urban growth system and to enable simulation of more realistic urban systems. To achieve this, the model introduces parameters to define the increase or decrease of growth coefficients. The details are as follows. The model sets a criterion - a growth rate - to decide the increase or decrease. It is a sum of urban growth produced by the four growth rules in one growth cycle, a year. This growth rate is compared to two threshold values: the critical high and critical low (the value can be amended by user). If the growth rate exceeds the critical high value, three coefficients (dispersion, spread, and breed) are multiplied by a parameter, called ‘boom’, greater than one. This encourages the system to grow more rapidly and simulates rapid urban growth. If the growth rate drops below the critical low value, the above three coefficients are multiplied by a parameter, termed ‘bust’, less than one. This makes the system grow slowly and represents little or no urban growth. If the growth rate stays between the critical high and low, two other coefficients (road gravity and slope) are modified accordingly. Since the self-modification rule works over different types of growth parameters, it not only affects the rate of urban growth at a global level but also influences the pattern of urban growth at the local scale. For instance, during the rapid or slow growth phase, when the growth rate goes over or below the critical values, independent new urban growth may be either promoted or demoted. During the normal growth, when the growth rate stays between the critical high and low, a road influenced urban growth pattern is likely to be the result.

5.3. Model Configuration for the Case Study

System Requirements and the Running Environment

The SLEUTH model is well documented and transparent enough to clearly understand its structure and behaviour. However, the learning curve is steep because the use of the model requires knowledge of the C programming language, cellular automata modelling, and GIS. It also involves prearrangement and pre-processing which are external to the model.

The model is written in the C language and designed to be used in a UNIX or UNIX-like system environment such as LINUX. Since the model is distributed as a set of source codes, a C compiler is also necessary to compile the codes. No specific hardware requirements are specified, but generally high performance computers are desirable because the model involves extensive computation.

This research has used a general purpose Windows based laptop computer with a 2.0 GHz dual core CPU and 4.0 GB memory for the implementation of SLEUTH. A way to run the SLEUTH model in a regular Windows system is to build a UNIX like environment. This is done by using a UNIX emulator such as Cygwin. It runs on Windows but opens a Bash shell[21] that

[21] Bash shell is an emulation of UNIX shell which is a command processor running in a text based window.

emulates the UNIX operating system. To compile the model, a standard GNU C compiler was separately installed in Cygwin.

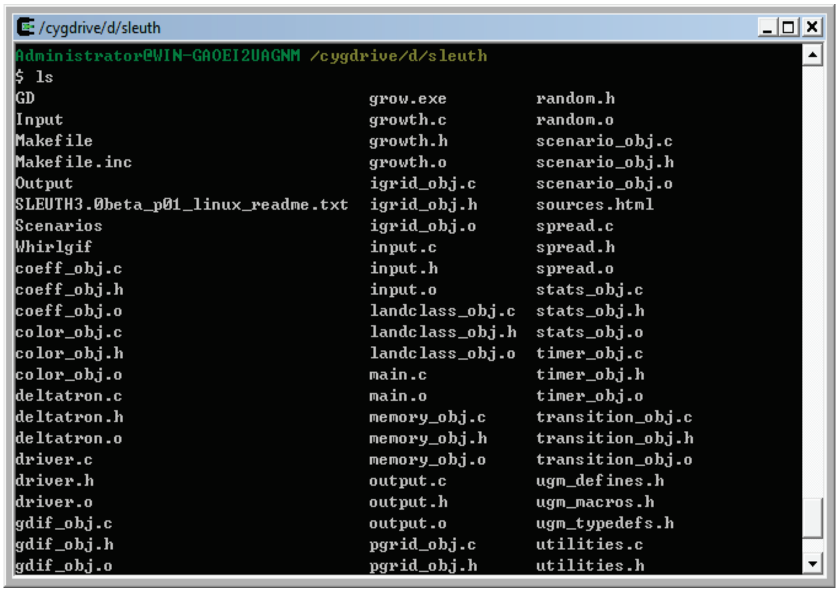


Figure 5.2. Cygwin Bash Shell and SLEUTH Source Codes

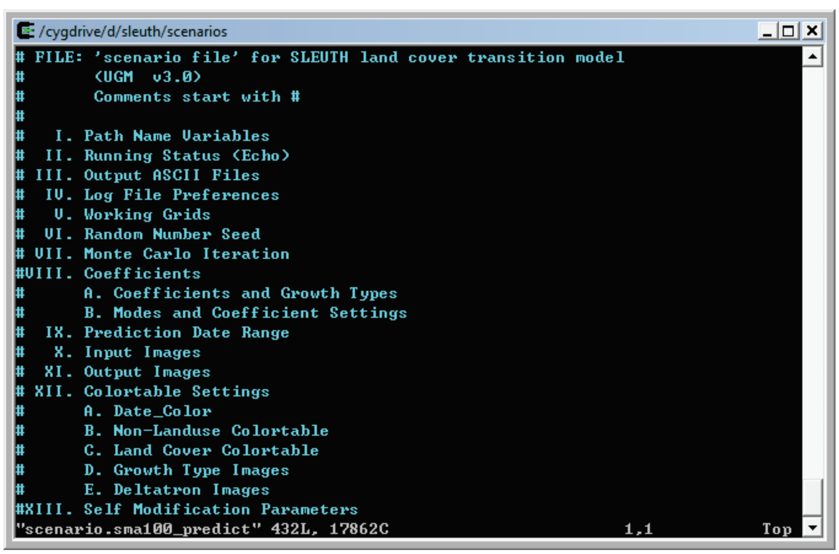


Figure 5.3. Contents of Scenario File

Once the source codes are compiled, the model is ready to use. However, although SLEUTH is a generic model open to end users for various applications, it does not have a GUI

(Graphical User Interface). The model is executed in the Cygwin Bash shell, and model parameter settings and all other configurations should be manually entered beforehand in what is called a scenario file. Then the model accordingly reads all necessary information from the file. A captured picture of the model interface is shown in Figure 5.2, and the contents of the scenario file are presented in Figure 5.3.

In addition, a link to a GIS application is crucial for implementing SLEUTH. The model does not have data processing capacity and relies on a loose coupling strategy. The raw data for required model inputs could exist in various formats, extents, and resolutions. At this point, raster based GIS data processing is fundamental to prepare input data as well as to examine output data. All data conversion and processing tasks are conducted using ESRI's ArcGIS in this research. Further image resampling works are conducted with Adobe Photoshop. Then input data are finally prepared in the 8-bit grayscale GIF format with the naming conventions specified by the model. Details about input data follow in the next section.

Input Data

SLEUTH runs over a grid space and derives model parameters from statistical analysis of raster based spatial data. Thus having good quality data is a first step in ensuring a successful implementation of SLEUTH. The sufficiency of data quality depends on the purpose of study but two things can be mentioned: contextual richness and spatial accuracy. The former deals with the factors considered in the simulation. For instance, it would be useful to include various levels of zoning regulation in the exclusion layer rather than simply to put natural urban growth barriers such as water bodies on the layer. Likewise, information about the different accessibility level of road networks would add useful realism to the single class road network. The latter determines the level of geometric representation. The cell size of the input data is the main factor here. Generally speaking, a coarse resolution omits details but a fine scale requires more time and cost for data gathering and processing.

In order to fulfill the data requirements and to produce rigorous modelling outcomes, the calibration of SLEUTH is often accompanied by dedicated data building, image processing to extract land cover classes from satellite imagery, and/or map digitising to draw road networks from various analogue sources. There is no doubt that the use of well-tailored and accurate data brings more realistic and rich implications for the study area. However, this study relied on what is called the best available data (BAD) obtainable from the public sector rather than a custom built data set.

> "……while the information that is available in professional practice is always bad - i.e., incomplete and inaccurate - it is also the best available data (BAD). This suggests that computer models that are developed to support planning should not require extensive data sets that are difficult, if not impossible, to obtain. Instead they should accommodate the data that are available in a particular location and use these data as best they can. This allows the power of computer-based planning support tools to be used not only by large, well-funded agencies, but also by smaller, data-poor communities……."(Klosterman, 2008)

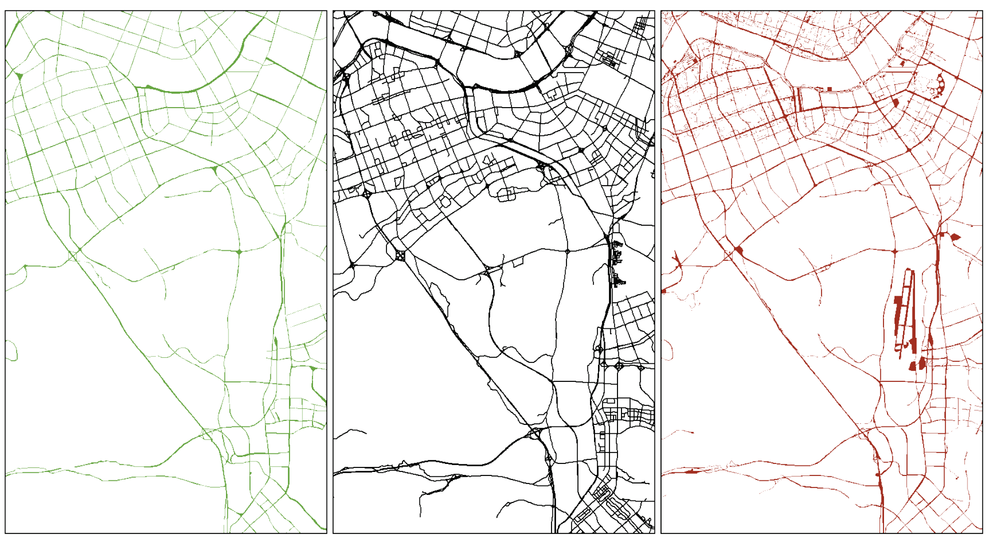
The study area used to test the model is SMA in Korea, an area covering 11,745 km^2. It is one of the most important areas for urban growth and sprawl in Korea. Thus the simulation with SLEUTH can provide insightful knowledge about the future of the study area. However, this research project was not able to find the data good enough for this simulation. After checking available digital data, the project realised that custom data building is a more desirable option to better calibrate the SLEUTH model. However, this project application to the SMA foundered on not being able to find data good enough for this simulation. After checking available digital data, we realised that custom data building would be the more desirable option to better calibrate the model. However, in order to minimise data preparation efforts, we decided to rely on the best available data even though we know that certain layers are incomplete and inaccurate. Inevitably this restricts the validity and usability of the simulation results. These issues with this input data will be further discussed later, but first descriptions about each input data and acquirement detail will be presented in the order in which we build and consider the layers in the acronym SLEUTH.

- The **S**lope layer can be typically processed from DEM (Digital Elevation Model) data. DEM is raster data in which each cell contains information about surface height. This study used the DEM data built and maintained by the National Geographic Information Institute in Korea and we utilised this to create the slope layer. The spatial resolution of original DEM data is 5m, and the base year is 2005.
- **L**and use data are not a requirement for the urban growth only simulation. However, this research used land cover data to extract other required input layers such as urban extent and excluded area. It is worth briefly mentioning the difference between land use and land cover data at this point. While the former classifies socio economic activities associated with land cover, the latter characterises physical characteristics of the earth's surface. Nevertheless there is a common overlap between two, and they are often used interchangeably. The Ministry of Environment in Korea produces different types of land cover data for the nation. What is called the 'low resolution version' has a resolution of 30 m and has 7 land categories. It is processed from Landsat TM (Thematic Mapper) imagery. 'mid resolution version' is processed from 2.5 m resolution SPOT 5 (Système Probatoire d'Observation de la Terre 5) and KOMPSAT-2 (Korea Multi-Purpose Satellite-2) imagery. This version of land cover data is however further refined by actual field survey and published in a vector format. This means it can be converted into any raster resolution. It has 22 categories of land cover which break down the former 7

categories of the low resolution version. The high resolution version uses 1 m spatial resolution imagery of KOMPSAT-2 (Korea Multi-Purpose Satellite-2) as source data. It has 41 land classifications which are further subdivided from the categories of the mid resolution version. But this high resolution only covers a part of the nation at the moment and in this project, we acquired the low resolution version for 1985, 1990, 1995, 2000, and 2006, and the mid resolution version for 2001 and 2009.

- The **E**xclusion layer was created from a combination of natural barrier and institutional regulations. The natural barrier simply included water bodies which are extracted from the low resolution version land cover data for 2006. Then this was combined with the greenbelt area which was obtained in vector format. A partial exclusion is not considered. The urban extent layer is extracted from the low resolution land cover data while the years chosen for the calibration are based on data at 1990, 1995, 2000, and 2006.
- The **T**ransportation layer was the most difficult input data to prepare for this simulation. Although various GIS data coverages covering a wide range of land use and transport data are commonly available nowadays, at least for the study area of the SMA, time series geographic data are extremely rare except for that processed from satellite imagery. In this project although we could obtain the whole road network data for the study area, (which is in vector format holding all information about road classes and types), we could not obtain dedicated historic transportation network data. Only a single time was available for the road data which is dated to the year 2005. At least two historic time points are necessary for model calibration. We consequently decided to use incomplete transportation data extracted from a series of land cover data. The alternative option was to extract the “transportation” category from the mid resolution land cover data. Two transportation layers, 2001 and 2009, were available as a result. However,

this transportation data has quality issues, for it is not strictly speaking considered as route data but as land use area data and thus difficult to use as a proxy for transport networks. As non-dedicated road data, this not only includes road networks but also auxiliary transportation facilities such as car parks and even airport runways. It is clear that this needs to be much refined if it is to be seriously used for urban development simulations. Besides, this extracted data do not have attribute information about road hierarchies. In this case, major motorways and local roads will have the same attractiveness level which is a somewhat unrealistic assumption. Despite these problems, we decided to use the data without custom manipulation since such corrections would have required significant time and cost with the quality of improvement still remaining in doubt. We show examples of the data in Figure 5.4.



2001(extracted from land cover) 2005(vector) 2009 (extracted from land cover)

Figure 5.4. Limitation of the Transportation Data Inputs

- Hillshade is a grey scale image that facilitates the interpretation of the terrain surface. If overlaid as a background, it greatly enhances visual readability of the base map. It is typically produced from DEM data using simple automatic functions in many GIS applications. The hillshade layer for this study was also created from the DEM data described above using a standard GIS package.

All source data were collected under such conditions, but deciding a suitable resolution for calibration and simulation was a difficult decision. Technically the finest resolution possible for this case is 30m, which is the low resolution version of the land cover data. Although other sources are available at a finer resolution, resampling the 30m resolution data to a finer scale is pointless. Thus, in estimating the computing power required and considering data quality, we initially adopted 50m resolution and prepared the input data accordingly. The grid dimension was 2650×3078 for the whole study area including the 'no data value' areas. However, the computer used for this simulation could not initiate the calibration, returning a memory error[22]. We then tried different levels of resolution and finally decided that 100m was an appropriate input data resolution. The grid size thus becomes 1325×1539 for the study area. Then the data were further re-sampled at 200m and 400m resolution for the calibration process, which is a requirement of the model. Details of input data layers are described in Table 5.1, and snapshot images of each layer are presented in Figure 5.5.

Table 5.1. Source Data and Descriptions

Layer	Source	Raw Data Provider	Original Resolution	Base Year
Slope	Processed from DEM	National Geographic Information Institute	5m	2005

[22] SLEUTH requires significant computing power. It is often necessary to use parallel computing or rewrite the source code to run the model for large areas at fine resolution.

Land Use	Extracted from Low Resolution Land Cover	Ministry of Environment	Vector	1990, 1995, 2000, 2006,
Excluded	Extracted from Low Resolution Land Cover	Ministry of Environment	30m	2006
Urban	Extracted from Low Resolution Land Cover	Ministry of Environment	30m	1990, 1995, 2000, 2006
Transportation	Extracted from Mid Resolution Land Cover	Ministry of Land, Transport, and Maritime Affairs	vector	2001, 2009
Hillshade	Processed from DEM	-	30m	2005

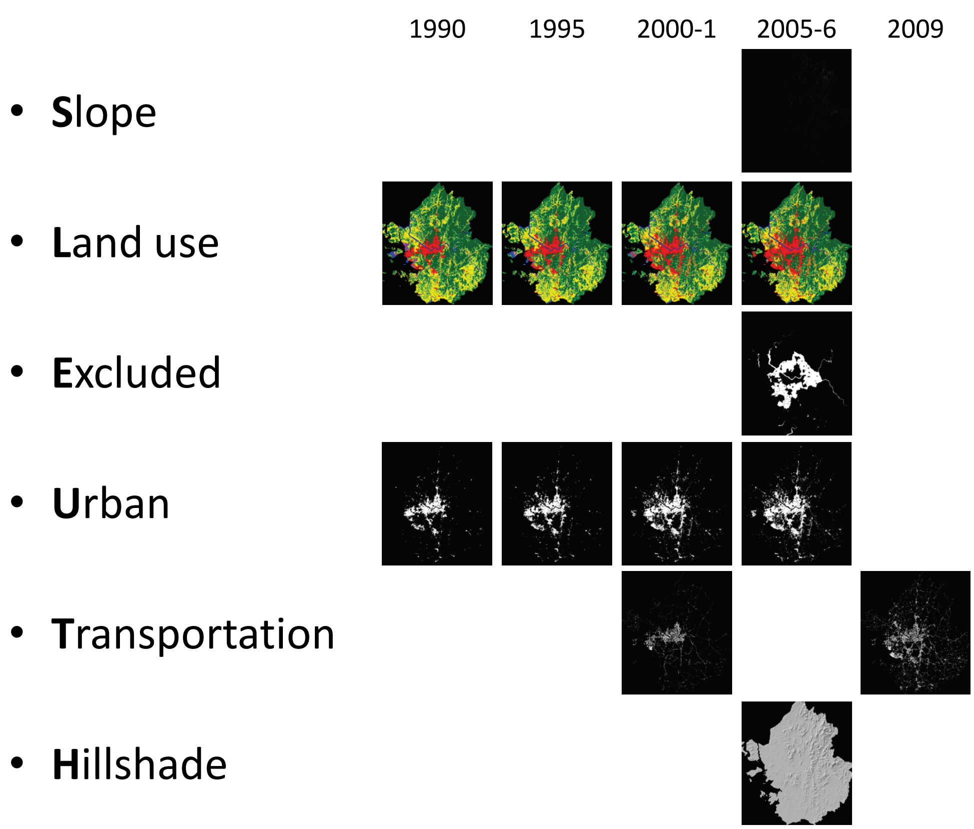


Figure 5.5. Visual Presentation of the Input Layers

Model Calibration

Running SLEUTH for predicting future urban growth requires the model to be calibrated beforehand. Generally speaking, the calibration of SLEUTH involves adapting the SLEUTH generic model to a particular study area by applying a parameter set unique to that area. More specifically, the main purpose of the calibration of SLEUTH in this case is to determine the best fit value for the five growth coefficients (dispersion, breed, spread, slope, and road gravity).

The calibration of SLEUTH is automatic and achieved by using a so called "brute force" algorithm[23] and supported by related statistical methods. Examining all possible cases until a solution is found is a useful problem-solving strategy, but it is only practically possible with the use of large scale computation requiring significant run time. During the calibration, all possible combinations of parameter values are applied to the past urban seed data and then the simulated results are checked against the historic urban data to see if the model reproduces known observed growth patterns.

However, SLEUTH does not automatically pick a single best fit parameter set as a result of calibration. During the calibration, the model creates 13 metrics which can be used to evaluate the goodness of fit between the simulated and observed. In more detail, SLEUTH produces statistical correlation scores for 13 predefined measurements along with each combination of five parameters. The measurement metrics include the total number of urban pixels, urban clusters, urban edges as well as other features. Details for the measurements are summarised in the Table 5.2.

[23] Brute force search is a general problem-solving technique in computer science. It involves searching and examining every candidate for the solution. It is a simple and effective approach, but the method requires considerable time as the number of candidates for the solution increases.

Table 5.2. Measurement Metrics provided by SLEUTH

Metrics	Descriptions
Product	All other scores multiplied together
Compare	Modelled population for final year / actual population for final year, or IF $P_{modelled} > P_{actual}$ [1 - (modelled population for final year / actual population for final year)]
Pop	Least squares regression scores for modelled urbanisation compared to actual urbanisation for the control years
Edges	Least squares regression score for modelled urban edge count compared to actual urban edge count for the control years
Clusters	Least squares regression score for modelled urban clustering compared to known urban clustering for the control years
Cluster size	Least squares regression score for modelled average urban cluster size compared to known average urban cluster size for the control years
LeeSalee	A shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years
Slope	Least squares regression of average slope for modelled urbanised cells compared to average slope of known urban cells for the control years
%urban	Least squares regression of percent of available pixels urbanised compared to the urbanised pixels for the control years
Xmean	Least squares regression of average x_values for modelled urbanised cells compared to average x_values of known urban cells for the control years
Ymean	Least squares regression of average y_values for modelled urbanised cells compared to average y_values of known urban cells for the control years
Rad	Least squares regression of average radius of the circle which encloses the urban pixels
FMatch	A proportion of goodness of fit across landuse classes. [#_modelled_LU correct / (#_modelled_LU correct + #_modelled_LU wrong)]

(Source: http://www.ncgia.ucsb.edu/projects/gig/About/dtDtControlDefine.html)

The overall calibration logic is the same as above, but the whole calibration process is broken down into three consecutive steps which gradually narrows the search range for optimal coefficient values and increases the resolution of input data. The ranges of each coefficient derived from the first step are entered into the second step and the same goes for the rest of the steps. The first calibration phase, termed coarse calibration, explores the entire range of coefficient values with large increments in parameter values. A quarter of the resolution images from the original full input resolution are used for this initial step. The second step, fine calibration, explores the narrowed coefficient values using a smaller increment. This step uses half resolution images and produces further narrowed coefficient values. The third step, final calibration, uses full resolution images and examines further narrowed ranges with a much smaller increment. Then, a single best fit parameter set is determined here.

However, the set determined in the final phase is not yet complete. It is not ready to be used for the prediction mode. Although the whole calibration consists of the above three steps, one more additional treatment is necessary to get the best fit parameter values for prediction runs. Due to the self-modification function of SLEUTH, these starting values of coefficients will be altered at the end of the simulation year. The self-modification increases or decreases the growth coefficient values as the simulation continues. To initialise the future simulation, it is desirable to use the values at the end year of the calibration rather than those at the beginning. A solution is thus obtained by using the best fit coefficients derived in the final phase and running the model again over the calibration period. Then the model will produce 'self-modified' coefficients. However, since SLEUTH deploys random cell transition algorithms, the results of each simulation run will be slightly varied as well as coefficient values being slightly modified at the end. Thus a Monte Carlo approximation is once again used here to take averaged finishing coefficient values. How many Monte Carlo iterations are enough remains an open question.

The calculation of statistical correlations for 13 metrics for every combination of parameters in each phase is automated, but the selection of a best range for the next step is a role for the user. The difficulty is that each of the 13 metrics compares different aspects of the spatial patterns. Thus there is no one right answer to evaluate the goodness of fit between the modelled and observed outcomes. Different researchers choose different measurements, but the LeeSallee metric has been among the most popular choices. However, recently Dietzel and Clarke (2007) have developed a new measurement, OSM (**O**ptimum **S**LEUTH **M**etric), and it has been claimed by the authors that the OSM is a better measure than other 13. The OSM is the product of the compare, population, edges, clusters, slope, X-mean, and Y-mean metrics (see Table 5.2).

Our research adopted the standard three step calibration process described above and used the OSM to evaluate a goodness of fit. The calibration was conducted over the data between 1990 and 2006. The initial phase was the coarse calibration. Re-sampled images with a resolution of 400m were used. The entire range from 0 to 100 of coefficient values was assigned with an increment step of 25. A low number, 4, of Monte Carlo iterations was assigned. The result of the coarse calibration phase was evaluated using the OSM, and then the ranges were selected from the top 5 scores. The result obtained in the coarse phase was then entered for the initial coefficient ranges of the second phase involving the fine calibration. The resolution of input images was reduced to a half from full resolution for this step, and the number of Monte Carlo iterations was increased to 7. The result was also analysed using the OSM, and then the ranges for the next phase were selected from the top 5 OSM scores. In the last phase, the final calibration, the ranges obtained from the fine calibration are applied to full resolution images. Now the aim is to determine a single best set rather than a range. The number of Monte Carlo iterations was increased to 10 for this step. As a result of this step, the best coefficients were selected from the top OSM score: 100 for the dispersion coefficient, 91 for the breed, 1 for the spread, 63 for the slope resistance, and 61 for the road gravity. However, since these are the best set for the beginning calibration year, the ones at the end of calibration after the self-modification step is made, are necessary for future simulation. A higher number of 100 Monte Carlo iterations were conducted to find the final coefficients for the prediction, which means 100 simulations were run with the best parameter set produced in the final stage and then the coefficient values presented at the end of the calibration year are averaged over 100. The chosen ranges for each coefficient in each step as well as the final values after the application of the self-modification rule are described in Table 5.3.

The parameters derived through such a calibration process characterise past urban growth patterns of the study area although these values are bounded by the quality of the input data. If this issue is not considered, some local characteristics can be inferred. A low value of the dispersion value implies that small scale urban sprawl is less dominant in the area. Low scores of the breed and spread coefficients show that such isolated urban developments are not likely to become spreading centres thus attracting new urban development in their surroundings. The high value of slope resistance tells us that the urban growth of the study area is greatly limited by topography. Finally, the low value of road gravity parameter implies that the urban growth in the area is less affected by transportation networks.

Table 5.3. Calibration Results

	Selected Values in Each Step			
	Coarse	Fine	Final	Self-modification
Dispersion	100-100	100-100	100	21
Breed	75-100	90-100	91	1
Spread	1-1	1-1	1	19
Slope	50-75	55-65	63	100
Road	50-100	60-70	61	1

5.4. Simulations

As a computer simulation model, SLEUTH can generate various alternative future urban growth patterns, supporting the exploration of diverse what-if policy scenarios. This can be achieved mainly through two options: changing parameter values and/or data inputs. The change of parameter values such as growth coefficients and self-modification parameters affects the growth rules and rates and results in alternative future growth. This option can also be used to assume the impact of certain growth types on overall growth systems. Numerous alternative scenarios are possible with this option but the practical meanings are clear when extreme changes in model parameters are taken into account. Incremental changes in model parameters will only give abstract meaning to alternative future growth. Another way is using different input data sets. This option is rather to assume different initial conditions and to see how the future is affected by this. Different levels of initial cell values can be assigned to the desired reference layers such as exclusion and transportation, or new elements can be added. Depending on what to include or exclude, this can be a more vivid option to address the change of certain policy directions for a given study area. SLEUTH does not use socio economic data and it only uses geographic data of the built environment. Thus the design of possible scenarios is limited to this. Different conditions can be considered only in a physical sense.

This study has designed two growth scenarios based on the second option: business as usual and deregulation of the greenbelt. The main difference is on the exclusion layer. One includes the greenbelt in the exclusion layer as usual in the past decades (see Figure 5.7.(a)). The other lifts the greenbelt restriction (see Figure 5.7.(b)). Followed by the calibration on data between 1990 and 2006, the prediction was run from 2006 to 2030[24]. Although the data used, especially the transportation layer, are incomplete and inaccurate, the model produced plausible results in comparison with the general characteristics of study area. Nonetheless seeking many practical implications from such input seems unjustifiable and thus has not been attempted. The results[25] are briefly described in this sense.

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[24] In order to save time for the simulation, 10 Monte Carlo runs were performed for these prediction runs. Generally, a large number of Monte Carlo iterations better approximate the result of simulations. However, there are no absolute criteria for the iteration number.

[25] SLEUTH provides both statistical and image outputs. The former includes the measurement

(a) Exclusion Layer with the Greenbelt (b) Exclusion Layer without the Greenbelt

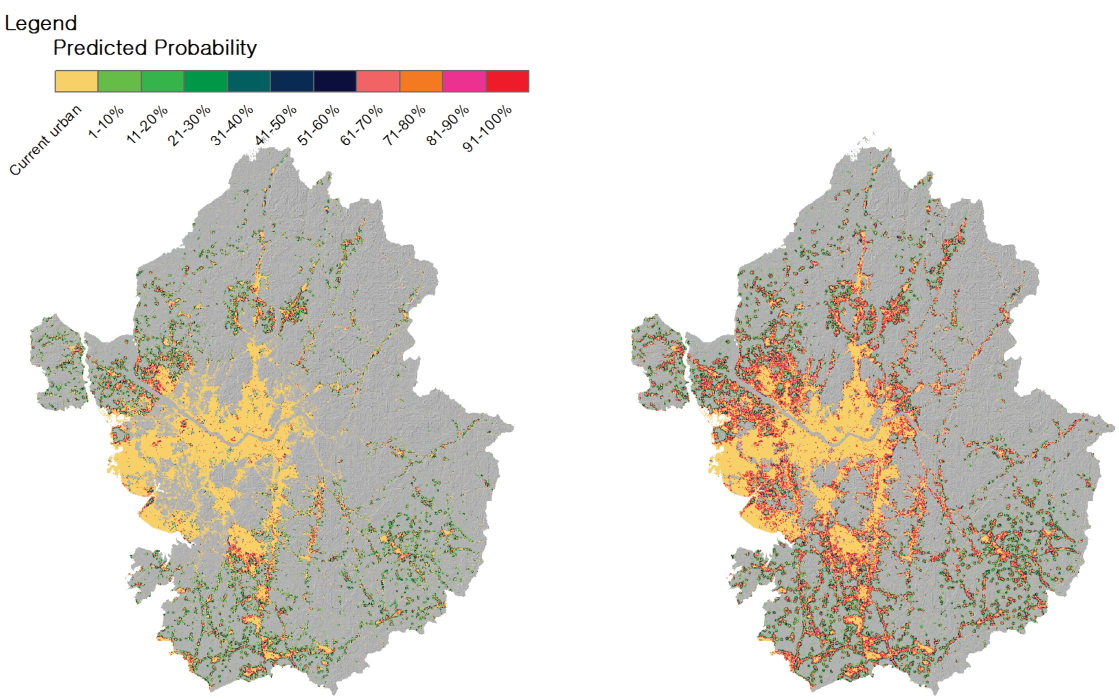
Figure 5.6. An Example of Different Exclusion Layers around Seoul

The first scenario assumes the future as an extension of past trends. The term 'business as usual' is often used to describe no particular additional intervention in the future, and this is often compared with other scenarios with intended policy actions. Typically no significant regional constraints are considered in the case of the business as usual scenario. However, since a greenbelt has protected the expansion of Seoul city over the past decades, such a constraint is included in the exclusion layer for this scenario. This scenario allows urban development to continue but restrains the growth in the designated greenbelt area. The total simulated urban area by 2030 in this scenario is approximately 2,264 km^2, and about 19.9% is urban in the whole study area. The net increase of urban land is 4.8 %, compared to the urban land in 2006. In terms

metrics described in Table 5.2, and the values are averaged over a specified number of Monte Carlo iterations. The latter includes a map which shows the probability of each cell becoming urbanised by the end of the simulation year.

of spatial allocation, this scenario generates less urban development around Seoul city but creates small urban clusters up and down the study area where slope values are relatively low. Such urban forms are more dominant in the areas outside the greenbelt implying leapfrogging sprawl.

The second scenario removes the greenbelt restriction while maintaining all other conditions used for the first scenario. This can allow maximum development for the region. In this scenario, the urban land increased from 15.1 % in 2006 to 27.5% in 2030. The total simulated urban area by 2030 is about 3,126 km^2. In terms of urban form, this scenario showed more clustered development around Seoul city. However, considering the growth rates and development patterns in the region during the past decades, this is too radical a pattern of urban growth and looks implausible. Moreover, new growth not only occurred in the removed green belt area but also in all other areas of the SMA.



(a) Business as Usual

(b) Greenbelt Removal

Figure 5.7. Results of Urban Growth Simulation at 2030

Table 5.4. Simulation Results by 2030

	Total Urban Cells 2006	Total Urban Cells 2030	Percent Urban Cells 2006	Percent Urban Cells 2030
Scenario (a)	171,774	226,406	15.1	19.9
Scenario (b)		312,555		27.5

The reason for such different growth patterns seems to be due to the values of the model parameters. The best parameter set which was derived when the greenbelt existed, worked for the first scenario but not for the second one. Thus a new parameter set is desirable for this scenario, but this possibility has not yet been attempted. This will be discussed in more detail in the concluding part of this chapter. Figure 5.7 and Table 5.4 presents the probability maps and summary statistics generated by the model, and they show comparative overall future growth patterns for the SMA under the two different scenarios.

5.5. Discussion

SLEUTH has been at the forefront of cellular automata urban simulation models. Not only as a research tool but also as a planning support instrument, the model has yielded useful policy implications for a variety of urban regions. In this study we calibrated SLEUTH for the SMA over historic data from 1990 to 2006. Then we simulated the future growth of the area from 2006 to 2030. Two growth scenarios, business as usual and greenbelt deregulation, were designed to explore alternative future growth. If more rigorously prepared and strictly calibrated, the simulation results in this study could also provide more pragmatic suggestions for future growth of the SMA. Although the results have limited practical meaning, this research does generate some thoughts about the calibration and application of SLEUTH for planning support.

It is not intended to criticise the model but to better promote the use of the urban model for planning support with necessary clarifications.

Firstly, as a cellular automata model, SLEUTH exemplifies how simple local level land use interaction results in complex urban behaviour. In addition, the model demonstrates that a range of supportive technological and scientific methods are also crucial to represent such urban systems. Urban growth is a result of complex interactions among social, economic, and environmental factors. Yet the succinct five rules of cell interactions at a micro scale effectively produce overall urban growth patterns even without taking the socio economic factors into account. At the same time, as a practical urban model, such cellular automata fundamentals are tightly supported by the GIS data and statistical analysis. The role of GIS is vital. But it is important to understand that such a role is more than an outsourced toolbox for data processing. The use of GIS data enables us to initiate model behaviour from an actual geography. In principle, the result of any cellular automata simulation is highly subject to the initial arrangements of cells and cell space. The use of GIS data confines such influencing initial conditions to an actual local geography. On the other hand the role of statistical analysis is also important in SLEUTH. The use of correlation statistics facilitates determination of valid parameters by providing a criterion to compare simulation outcomes and actual historic patterns. Although there is no one right way to decide the best fit model parameters, the selection of model parameters firmly stands on empirical grounds. Combined together, SLEUTH proves how cellular automata based urban models can replicate realistic urban system behaviour with rich practical implications.

Secondly, however, a complicated data issue arises for successful implementation of SLEUTH. It is clear that inadequate data would result in poor calibration and simulation results. The model is tightly based on the use and analysis of empirical data. Hence the quantity and quality of input data do matter. SLEUTH does not require comprehensive spatial and/or aspatial data, but this study faced a major difficulty with gathering historic data, especially for the transportation networks. Fulfilling these data requirements is a necessary step to use the generic model, although such data requirements are not a shortcoming of SLEUTH at all. However, it is one thing that the urban modelling community should collectively think about. SLEUTH does not necessarily require fine scale data. However, if nothing else is considered such as computing power and calculation time, a finer scale is preferred for SLEUTH because the model derives its parameters by analysing mapped physical urban forms only. Finding a right resolution for a given study area is more of a practical decision. However, it is important to note that there are pitfalls in the use of raster based GIS data. The raster data processing such as a conversion from vector source and resampling to lower resolution involves generalisation and approximation. This could drop numbers of small urban isolations or narrow road networks, which are indeed important factors for local level transitions. This implies that a possibility of choosing the best fit parameter set greatly depends on the nature of raster data used as well as the data handling process.

Thirdly, it is also important to understand the nature of the best fit parameter set. The 14 measurements, including the 13 metrics automatically being created by the model and the Optimum SLEUTH Metric (OSM) being calculated externally, summarises the system characteristics at an aggregate global scale. This statistical representation may be practically and methodologically the best way available to investigate the modelled results in a reliable and objective fashion, but such measurements omit the investigation of heterogeneous local characteristics in the system. The best parameter set determined by considering such measurements has a firm statistical representativeness. However, the simulated future from these parameters is an extension from the aggregated and averaged model outcomes, not from local peculiarities.

Although some clarifications are necessary in the use of such cellular automata models for planning support, this research has demonstrated that there is no doubt that cellular automata urban models have a significant strength in capturing dynamic patterns and processes of urban growth. It also witnessed that a cellular automata urban model could better be enhanced by incorporating various methods and technologies as shown in the case of SLEUTH model. One last thing this study would like to document is an anomaly observed with regard to the use of the model for alternative scenarios.

A computer simulation model can act like a virtual laboratory which enables the exploration of various 'what-if' scenarios. However, consideration of a certain policy intervention which can abruptly alter future growth trends over the best parameter set derived from the past patterns can return unexpected results. As shown in the simulations in this study, the parameter set derived from analysing past patterns worked with the scenario of no change but produced too much growth in the outcomes for the scenario based on greenbelt removal. A new calibration with an improved data set and close examination of why this happened could be a possible future extension of this simulation.

Chapter 6: Experimental Simulation 2: The Metronamica Model

6.1. Background of Simulation

Metronamica is a cellular automata based land use change model, developed and managed by the Research Institute for Knowledge Systems (RIKS). The model is built upon the pioneering work of White and Engelen (1993) and White et al (1997) which introduced a constrained and integrated cellular automata urban model. The model was firstly applied to the city of Cincinnati, USA. Up until now, it has been applied to a large number of cities and regions around the world, including Dublin (Ireland), Milan (Italy), Wuhan (China), Vitoria-Gasteiz (Spain), and in many other places where land use change dynamics and possible consequences of alternative policy options have been simulated (RIKS, 2011). After continued development, it is now a planning support system equipped with distinctive extensions and modelling modules. Nevertheless the behaviour of the cellular automata model, which is the main focus of this research, forms the core of the Metronamica model. The model is designed to study changes among multiple land use classes, but it is also possible to focus on the dynamics of urban and non-urban land conversion.

The purpose of our presentation of urban growth simulation with Metronamica in this chapter is twofold: to calibrate the model for a case study area for practical policy support and to explore the methodological implications through such an empirical application.

Firstly, this research seeks to forecast future urban growth trends of the study area, the SMA in Korea[26]. The model is calibrated to capture the key driving forces of past growth

[26] The simulation work in this research was supported by a project from the OECD (Organisation for Economic Co-operation and Development). The project involved showing how new kinds of widely available land development models based on CA might inform planning policy in the Korean urban context.

patterns and then the observed patterns are used to simulate future growth. More importantly, the research assumes different planning scenarios to explore possible consequences of how future urban growth is likely to be affected by possible planning policies. The three scenarios which were designed were not based on abstract ideas but reflected the actual planning policy agenda for the study area. Although the model is not designed to seek exact trajectories of spatial change, it presents possible urban growth future states of the study area which are firmly based upon scientific methods and logical assumptions.

Secondly, the research attempts to draw methodological implications from such model calibration and empirical application. Metronamica introduces ranges of innovative methods into the cellular automata framework. Most importantly, whereas conventional cellular automata models are purely physical, Metronamica incorporates socio-economic features. This addresses the very heart of cellular automata models – uncontrolled local behaviour. Land use dynamics is no longer a result of local level interaction between cells but is also regulated by a top down force. This research demonstrates how such integration can be achieved and discusses how it augments and limits traditional cellular automata behaviour. The model has a unique structure and interpretation of the system under study. The strengths and limitations inherited from the unique modelling approach is evaluated at the end of this chapter. However, we are not strictly evaluating the performance of the model but simply gaining a better understanding of cellular automata urban models.

To attain these goals, this study firstly examines the structure and behaviour of the Metronamica model. Its unique features are analysed and described. Then we carry out model calibration and simulation for the study area. The results of the simulations are followed by a detailed description of each scenario. The chapter then concludes with a discussion of Metronamica and cellular automata urban models in general.

6.2. Model Description

Model Structure and Behaviour

Metronamica is an integrated planning support system which has a range of extensions such as transport, macro-economics, demographics, and other custom built plug-ins. Besides the main body of Metronamica, the model works in one of two configurations, that is either in the single layer (SL) or multi layer (ML) version which have different levels of spatial representation within the modelling framework. In total the model has three conceptual modelling layers which each represent different spatial levels: global, regional, and local. At the local level, a cellular automata model simulates land use dynamics. Then at the regional level, a spatial interaction model incorporates the changes in population and employment. Finally the global level, which incorporates exogenous parameters, controls the overall quantity of system change. The single layer version integrates the local level land use dynamics and global level constraints. The multilayer version takes all three levels into account. Indeed, the ML version is not a sole cellular automata urban model but rather an integration of cellular automata and spatial interaction models. This research uses the single layer version and hence refers to Metronamica as a single layer version without additional extensions.

Metronamica employs the basic principles of cellular automata modelling but greatly relies on a series of innovative methods whereas SLEUTH is simpler and more traditional. Three key characteristics distinguish the Metronamica model from conventional cellular automata models: distance decay functions, integration with GIS, and constrained cell transition. Before explaining the model structure in detail, it is important to discuss such key characteristics. These three key building blocks of the model are depicted in Figure 6.1 and the descriptions are as follows.

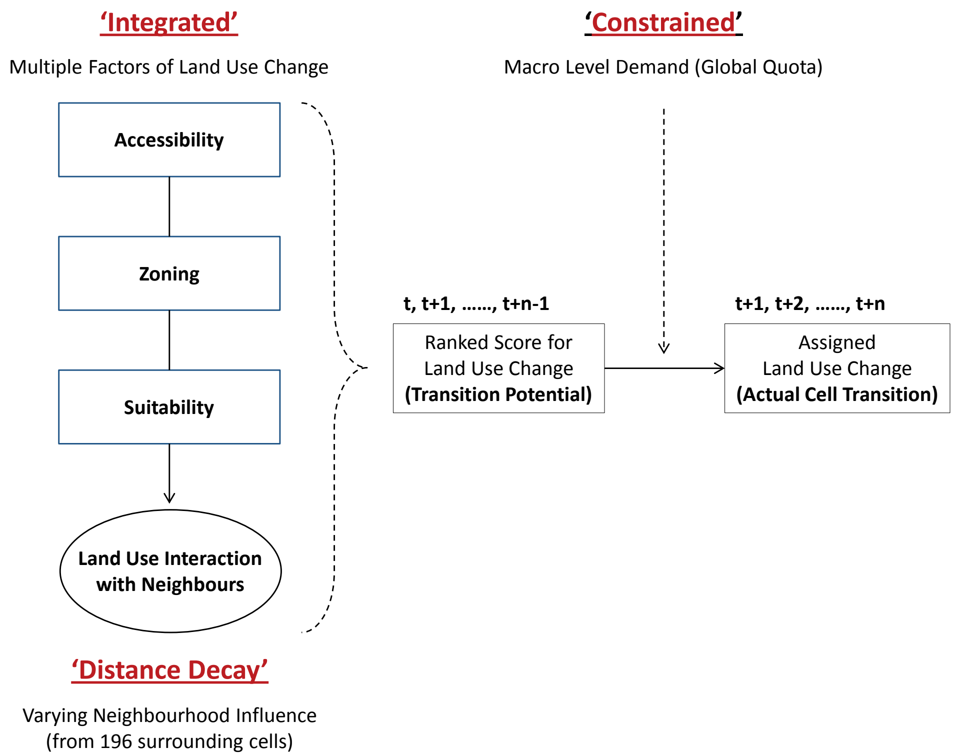


Figure 6.1. The Local Dynamics of Metronamica

Firstly, the model uses a larger concentric neighbourhood configuration and incorporates the notion of distance decay into its modelling framework to define the relationship between a cell and its neighbours. The concept is based on Waldo Tobler's First Law of Geography: "Everything is related to everything else, but near things are more related than distant things."(Tobler, 1970). Conventional cellular automata models usually use either 4-cell von Neumann or 8-cell Moore neighbourhood configurations. Here only immediately adjacent cells - the Moore neighbourhood - are considered as a neighbourhood and affect the centre cell's transition. However, it is more realistic to assume a larger neighbourhood interaction in the case of urban models because a land use state is not only affected by its immediate surroundings but also by features in more remote locations. To this end, Metronamica defines the size of a 196-cell concentric neighbourhood, a radius of 8 cells from the centre cell, as a default neighbourhood although its size can be adjusted as a model parameter. The centre cell has a one-to-many relationship in the neighbourhood, and the strength of this relationship generally diminishes as the distance increases thus implying distance decay. The collective influence from all cells to the centre cell in a given neighbourhood is defined as a neighbourhood effect in the model. Defining the degree and magnitude of such neighbourhood effects is a matter of model calibration, and this will be discussed later. It is worth noting that it is this property that destroys the concept of strict emergence in the model and forces comparisons to LUTI models in which interaction fields based on distance decay are central to the notion of the way cities and regions are organised. The argument is often made that if cellular automata models are relaxed in this way, they lose their pedagogic and informative value in terms of simulating emergence.

Secondly, the model integrates the cellular automata modelling framework with GIS technology. The use of GIS data not only makes it possible to initiate the model from within the actual geography but also suggests a way of taking into account the effect of various driving forces contributing to land use change dynamics. In addition to the interaction within the neighbourhood, Metronamica further integrates GIS data in order to introduce the influence of additional key factors: zoning, suitability, and accessibility. Consequently the model assumes that land use change is jointly brought about by an interaction between four major factors: spatial interaction with surrounding land uses, zoning, suitability, and accessibility. On the other hand the integration of GIS does not necessarily only mean the use of GIS data. The model also incorporates GIS technologies to analyse and visualise input data as well as model outcomes.

Thirdly, the model constrains the total amount of cell transitions through the use of exogenous variables. In a general cellular automata system, cell transition is only governed by local interactions, not by other mechanisms. This then leads to an unexpected global level outcome. The constrained cellular automata model Metronamica globally regulates the occurrence of local patterns. In other words, the model does not sum up all possible changes at the local level. The model calculates a ranked score for each cell and then makes an allocation considering the total amount defined. The rank score, termed transition potential, is calculated for each cell in each time step by using the above four major factors: spatial relationships with surrounding land uses, overlaid zoning, suitability, and accessibility information. No matter how high the transition potential, the cell's future transition can be limited depending on its exogenous parameters. In this way only limited numbers of cells are allowed for state change in each time step. The merit of this approach is that the model can incorporate meaningful indicative values from various socio-economic macro models and data. For instance, the exogenous parameter can have meaning for macro level land use demand.

Built on the above conceptual framework, the following equations best describe key determinants of the transition potential in detail as well as the elements of model calibration.

$$\hat{N}_{ij} = \begin{cases} N_{ij}(1+e), & if\ \alpha \geq 0 \\ N_{ij}, & else \end{cases} \tag{6.1}$$

$$T_{ij} = \begin{cases} \hat{N}_{ij}\, S_{ij} Z_{ij} A_{ij}, & if\ \hat{N}_{ij} \geq 0 \\ \hat{N}_{ij} \left(2 - S_{ij} Z_{ij} A_{ij}\right), & else \end{cases} \tag{6.2}$$

where N_{ij} represents the neighbourhood potential in a cell *i* for an actively changeable land use class *j* before the consideration of a random perturbation effect. α is a parameter which decides the existence and extent of the stochastic perturbation [0, 1], and *e* is a random value taken from a Weibull distribution (1/ α, 1). $\hat{N}_{ij}$ is the neighbourhood potential after taking into account the random effect. Respectively in the cell *i* for the land use class *j*, S_{ij} is the suitability, Z_{ij} denotes the zoning, and A_{ij} stands for the accessibility. T_{ij} is the resulting transition potential score which varies with the four main factors as well as consideration of the random disturbance.

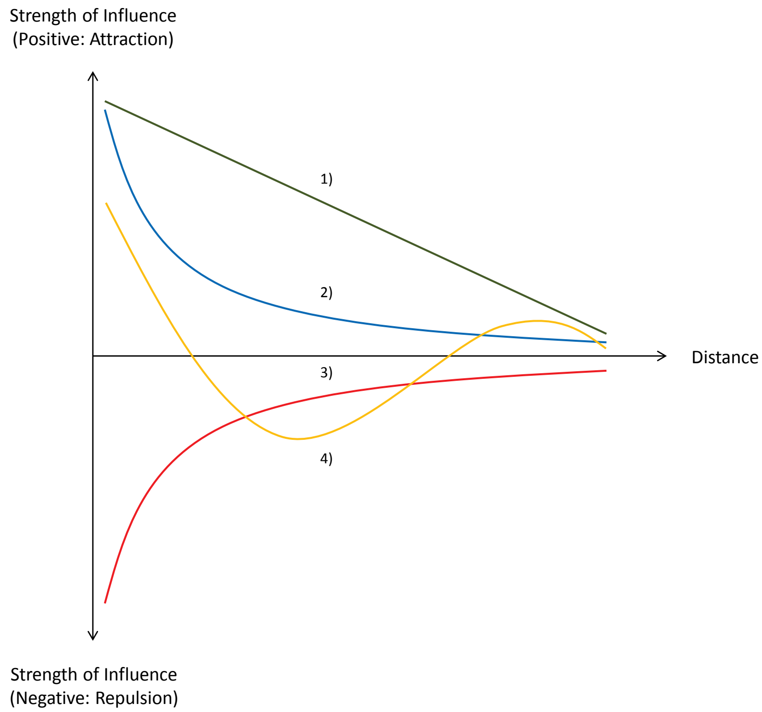
The neighbourhood potential forms the core of the transition potential, while the three other factors augment the cellular automata dynamics by bringing essential factors relevant to land use change. It is worth investigating the neighbourhood effect in more detail. The neighbourhood effect is defined by:

$$N_{ij} = \sum_{b \in S(a)} I(a,b,d) D(a,b) \tag{6.3}$$

where *S(a)* represents the neighbourhood of a cell *a*, *b* is a member of *S(a)*, and *D(a, b)* is the Euclidian distance between the cell *a* and *b*. *I (a, b, d)* is the influence function describing the style and strength of relationship between the cell *a* and *b,* which is also affected by the distance *d* between cell *a* and *b*.

Thus the neighbourhood potential is the sum of the distance and influence function for each cell in the neighbourhood. The use of a fixed neighbourhood size for all cells in the study space and Euclidian distance between one cell to another implies that the influence function is a key parameter for determining the neighbourhood potential but users need to be immersed in their own application so that unique rule sets can be identified.

One land use type may attract or repulse another type by varying degrees. All cells in the neighbourhood are related to the centre cell in one way or another. In general cells in nearer locations in the neighbourhood will have a larger influence. However, an opposite case also exists, and such an effect is not likely always to be linear. Figure 6.2 presents some of many possible neighbourhood effects. Thus, identifying/defining such relationships is one important element of the calibration of Metronamica model. The model provides some predefined rule sets which describes the influence relationship between land uses in order to facilitate the calibration process.



1) General distance decay: the influence gradually diminishing with distance

2) Attraction: positive clustering at a closer distance

3) Repulsion: clustering of ‘avoidance’ at a closer distance

4) Fluctuation: attraction to close neighbours but repulsion from neighbours in mid distance and then attraction again to distant neighbourhoods.

Figure 6.2. Examples of the Neighbourhood Effects

In summary, the total amount of land use change is firstly defined by an exogenous constraining parameter at the macro level. Then the model calculates the likelihood of land use change, namely transition potential, for each cell. The transition potential is a rank score which is a multiplication of neighbourhood potential, suitability, zoning, accessibility, and optionally a stochastic perturbation. Based on this score, the model allows the state change from the top rankings. The cut line which regulates the total quantity of change is determined by an exogenously defined global constraint.

Data Requirements

Metronamica requires four types of input data layers to simulate local level land use dynamics: land use, suitability, zoning, and transportation. Each input layer represents the four main driving forces of land use change. Technically a boundary layer for the study area is also necessary but this is to define the overall modelling area.

The land use data layer forms a basis for cell transition dynamics. Initially the land use layer may have different classification systems depending on the source data. But each land use class must be reclassified into three categories in the Metronamica modelling environment by the following order: vacant, function, and feature. The vacant category is composed of the land use classes that can be passively taken over by the expansion of the classes in the function category. The function category consists of the classes actively changing during the simulation. The feature category includes the classes not subject to the future change. The simulation runs on data for a single recent year, but time series data are necessary for the calibration in order to compare the simulation result from a seed year to observed data at the target year. Metronamica requires only two base years of the land use map for model calibration. This is due to a manual and qualitative calibration process of the model. The details of model calibration will be discussed in the next section.

The suitability layer defines to what degree a cell is suitable for a particular active land use activity. The level of suitability is evaluated by mainly considering physical and environmental aspects of the study area. Metronamica supports the creation of the suitability layer by overlaying a range of input factor maps. A DEM (Digital Elevation Model) is one minimum requirement to produce the suitability layer, but it is possible to consider more factors such as slope, aspect, soil quality, natural hazard, pollution, and other desired map layers that are relevant to a study area. The determination of a suitability score is the modeller's role. The layer holds composite scores for each cell ranging from 0 to 10, and the scores remain constant during the simulation.

The zoning layer depicts spatial regulation or permission associated with certain land uses. Similar but contrary to the physical suitability layer, this layer represents institutional suitability. The layer can be created in the model from various local, regional, national plans and policies relevant to the study area. This layer also ultimately holds a composite score which ranges from 0 to 3. However, while the physical suitability stays static over the time, this institutional suitability score is dynamically introduced to the simulation. Associated land use functions can be permitted from the beginning of the simulation year or from desired time points in the future.

The accessibility layer includes various transportation networks such as road and railway in order to consider the influence of transportation on the actively modelled land use functions. The degree of influence can be determined by users along with different sub classes of network. Multiple time periods of transportation data that show the historic changes are desirable but not mandatory for the calibration.

All input layers should have the same spatial extent and resolution as typical in raster cell-based models. In terms of data format, Metronamica requires Arc ASCII (asc) or Idrisi raster (rst) format except for the transportation layer. The model requires vector data for the transportation layer, and ESRI shape file format (shp) is the designated format. Metronamica has in-built data processing capacity although it is not as powerful as the ones in external GIS applications. Certain input layers such as the suitability and zoning can be processed externally with GIS applications or internally in the modelling environment.

The above data so far outlined include the requirements for local level dynamics. One last form of input data also has an important role. Recall that the model has multiple spatial representations and the exogenous constraint is defined at the global level. The nature of the global constraint is taken from data unless it is assigned in an arbitrary manner. How to define such data is of course exogenous to the model, and it varies across applications. One approach will be presented along with the actual simulation results in this chapter.

6.3. The Model Configuration for the Case Study

System Requirements and the Run Time Environment

The Metronamica model runs on a general Windows-based computer system, and an additional platform or compiler is not necessary. The initial arrangement to use the model is to install the software, as is usual for general Windows applications. Two minimum system requirements specified by the RIKS are a minimum 512 MB memory and 1 GB free space in the hard disk.

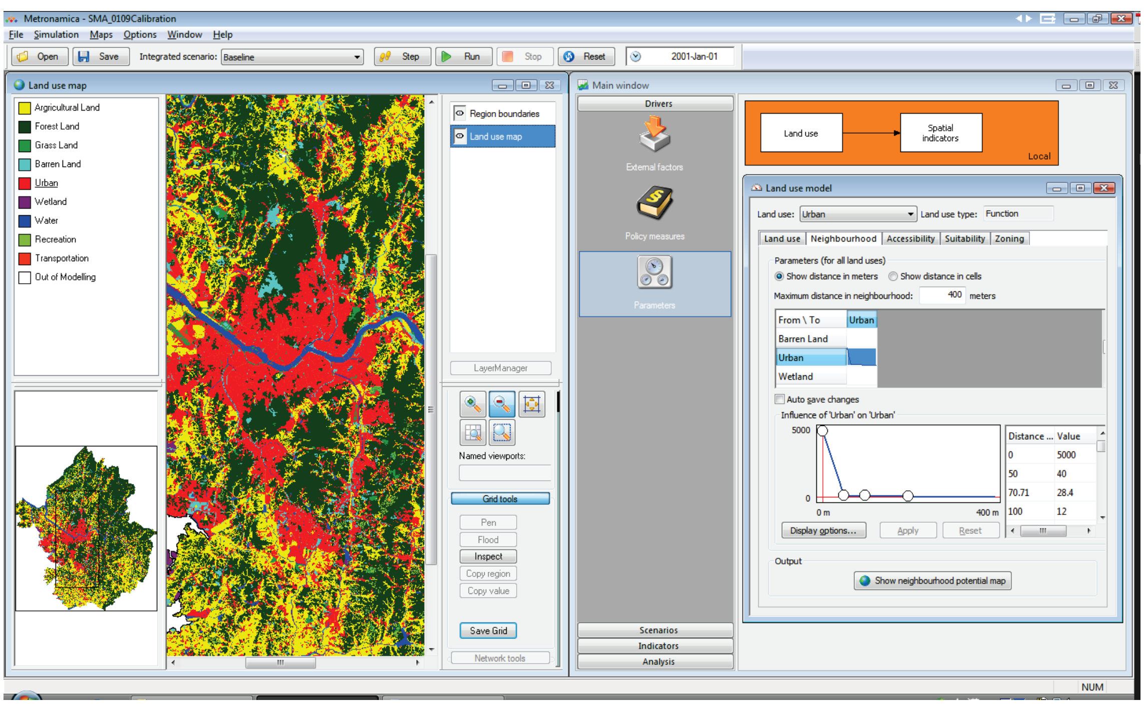


Figure 6.3. The Metronamica Modelling Environment

Metronamica works in a full GUI menu interface. Most modelling mechanisms including parameter input and change are achieved in the visual environment. No prior knowledge of computer programming is necessary although an understanding of the cellular automata modelling framework and raster GIS data model is essential to implementing Metronamica as is usual for the implementation of any cellular automata based urban model. The GUI based modelling environment of Metronamica is shown in Figure 6.3.

A loose coupling with a GIS application is not critical as the model has a certain capacity for spatial data processing and visualisation. However, the use of external supportive applications such as spreadsheets, image viewers, and other GIS are desirable for more efficient modelling work, especially for model calibration and the analysis of model results.

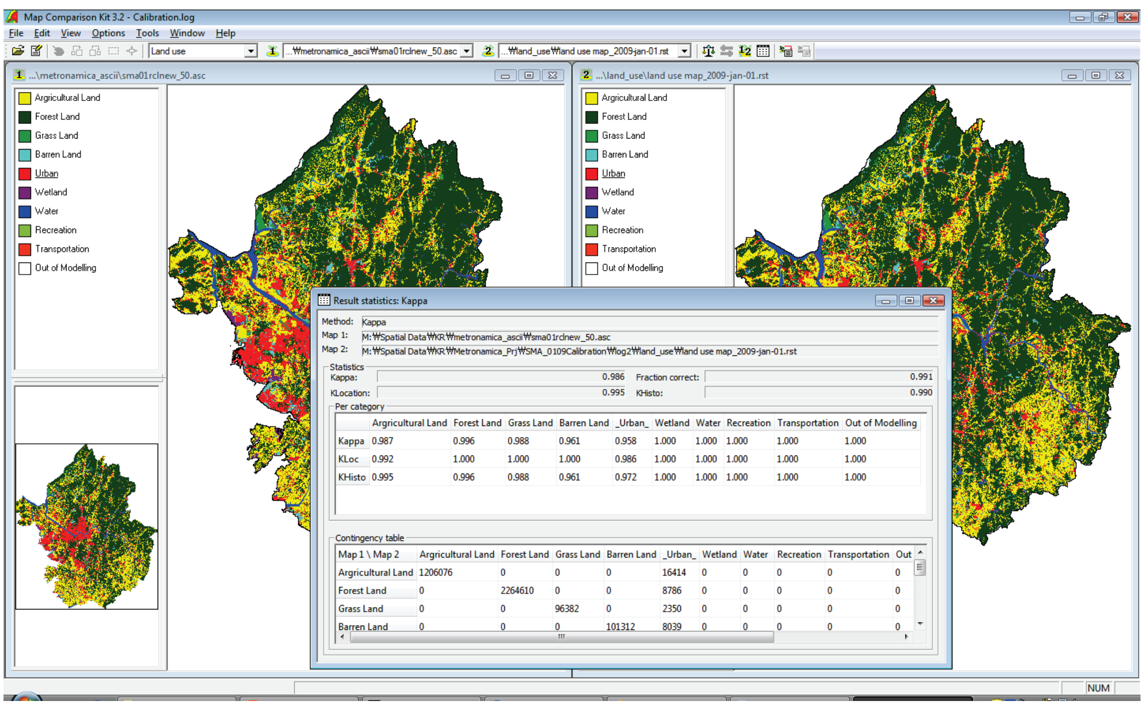


Figure 6.4. The Interface of the Map Comparison Kit

Since Metronamica does not have a devoted module or function for the calibration, the calibration is achieved by running a simulation from a past seed year to a recently observed target year. Many simulation results generated from various parameters are externally compared to empirical data. The Map Comparison Kit (MCK) is a useful application to conduct such comparisons. It is a non-proprietary software tool developed and distributed also by RIKS to support the raster map comparison. It not only supports visual examination of the modelling results but also provides useful cell comparision metrics such as the Kappa index. A screen capture of the MCK is provided in Figure 6.4.

Another application, Fragstats, is also a useful tool to evaluate simulation outcomes. It is a spatial pattern analysis application initially developed in the Oregon State University and then further refined in the UMass Landscape Ecology Lab (McGarigal, Cushman, Neel, and Ene, 2002). It calculates a range of landscape metrics such as the shape metrics from categorical input maps.

This research installed Metronamica in a Windows based notebook computer which has a 2.0 GHz dual core CPU and 4.0 GB memory. ESRI ArcGIS was mainly used to prepare input data, but the research used the Map Comparison Kit to carry out model calibration and the Fragstats software to evaluate the simulation results generated by different scenarios.

Input Data

Metronamica requires five GIS based input layers: land use, suitability, zoning, accessibility, and the boundary. Layers such as suitability and zoning are actually value added information that hold composite scores. In that case, the layer requires additional input factor data. This study relied on the data available from the public sector rather than custom built data. Although there was an accuracy problem such as inconsistencies between land use maps at different years, generally fine scale spatial data were available for the given study area. The study area for this simulation is the same as for SLEUTH above, the Seoul Metropolitan Area (SMA). The following section describes the data set used for model calibration and simulation runs for the study area, some of which was used in the previous chapter in the SLEUTH application.

For the land use map, what is called the 'mid resolution land cover data' produced by the Ministry of Environment in Korea was used. We will repeat the data specification to remind the reader of the nature of these data. Such land cover data are fundamentally based on the 2.5 m resolution SPOT 5 (Système Probatoire d'Observation de la Terre 5) and KOMPSAT-2 (Korea Multi-Purpose Satellite-2) imagery but published in vector format after refining the data by a back up field survey. The mid resolution land cover map originally had 22 land classes, but it was reclassified into 9 categories for this simulation: agriculture, forest, grass, barren, urban, wetland, water, recreation[27], and transportation. Then each of these was assigned to three land categories which is a requirement of the Metronamica model. Since the urban growth simulation is targeted, the function category includes only one land use class, urban. The vacant category consists of agriculture, forest, grass, and barren land. This means that land uses in this category are available for future urban growth. The feature category is composed of wetland, water, recreation, and transportation. The land uses in this group will remain static during the simulation. The land use map for 2001 was used as a seed layer for the calibration, and the results were compared to 2009 data. Then the 2009 map was used as a seed for the future simulation.

The suitability layer mainly took account of the terrain condition of the study area. It was created by jointly considering the height and slope condition. After firstly excluding the area over 200m, it classified the area into four categories with percentage slope values. The area with a slope over 20 percent was set to have 0 value, which excluded it from urban growth. The slope values from 20 to 11 and 10 to 5 were assigned to 2 and 1 respectively. The values from 5 to 0 were classified as 3, which meant the lowest topographical resistance.

[27] This includes open space not subject to urban growth such as golf courses and theme parks.

The zoning layer included greenbelt information which is the most important spatial regulation in the study area. Except for the area protected by the greenbelt, future urban growth is permitted without further restrictions. Two different versions of greenbelt data were prepared in order to assume different planning scenarios. One represented the currently active greenbelt. The other reflected possible adjustments which are part of an ongoing planning policy agenda for the study area. Detailed descriptions will be dealt with in the relevant scenario section.

The accessibility layer used comprehensive road network data for the study area. The level of accessibility was defined into 4 levels depending on the type of roads: highway, major road, minor road, and local road. In addition, the newly proposed high speed railway routes and stations were prepared for an alternative scenario to simulate the impact of such a new railway system. The details of this will also be described along with the relevant scenario.

A spatial resolution of 50m was decided for the simulation. Generally finer scale data better describes geographic details but there is a trade-off between data resolution and computing resources. Technically the finest resolution possible for this simulation is 5m (see Table 6.1). However such fine scale was never likely to be practical for this study. The research initially tried to run the calibration with 25m resolution data which gives a grid size of 5292×6168 for the whole study area. However as with SLEUTH the system could not be run at this level of resolution. After exploring alternatives, we finally decided to use 50m resolution, which gives a grid size of 2649×3084 in this case. Details of input data are presented in Table 6.1 and Figure 6.5.

Table 6.1. Input Data and Descriptions

Layer	Source	Raw Data Provider	Original Resolution	Base Year
Land Use	Reclassified from Mid Resolution Land Cover	Ministry of Environment	Vector	2001, 2009

Suitability	DEM	Original	National Geographic Information Institute	5m	2005
	Slope	Converted from DEM	National Geographic Information Institute	5m	2005
	Water Body	Extracted from Mid Resolution Land Cover	Ministry of Environment	Vector	2009
Zoning	Greenbelt	Original	Ministry of Land, Transport, and Maritime Affairs	Vector	2008
	Greenbelt Adjustment	Original	Ministry of Land, Transport, and Maritime Affairs	Vector	2010
Accessibility	Road Networks	Original	Ministry of Land, Transport, and Maritime Affairs	Vector	2005
	GTX[a] Routes and Stations	Original	Gyeonggi-Do[b]	Vector	2013
Area Boundary		Processed from Administrative Boundary	National Statistical Office	Vector	2005

[a]Stands for Great Train eXpress, which is a new metropolitan high speed rail system currently under planning for the study area.

[b]Local government that covers most of the study area except for Seoul and Incheon city.

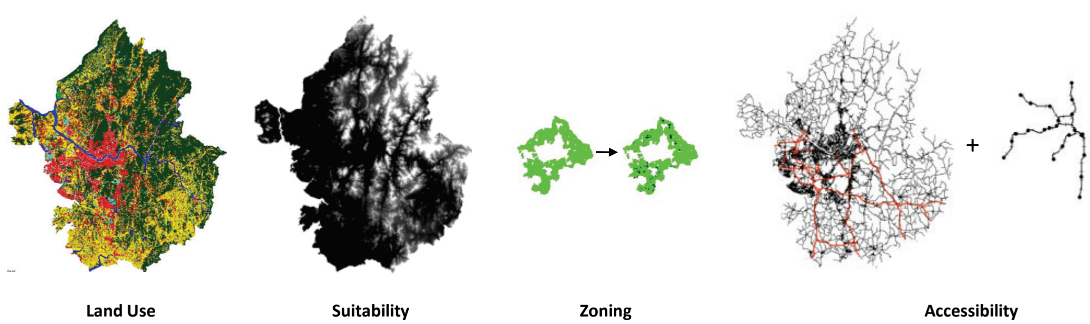


Figure 6.5. Input Layers for Calibration and Future Simulation

Model Calibration

The calibration of Metronamica is manual, qualitative, and partial. It is qualitative because it involves decisions based on deep understanding of the study area rather than on quantified figures. It is partial in that it is only applicable to local level dynamics. The global constraint which will regulate future local behaviour cannot be derived as a result of model calibration. Such characteristics are basically due to the complex nature of the model structure and the difficulty of estimating different strata of parameter values from single observed data of the land use map. An automatic extraction has been attempted (Straatman, White, and Engelen), but so far no single method has replaced a human knowledge oriented calibration process specific to the Metronamica model. However, this does not necessarily mean this calibration and hence the simulation result is unreliable. Compared to an automatic calibration based on statistical techniques, the qualitative calibration has a clear advantage in presenting human knowledge on spatial form and pattern specific to the modelled area. Indeed this is a *de facto* method that enables the close examination of the local level patterns since no quantitative metrics can yet fully replace such a method.

Nonetheless, the calibration process of Metronamica can be generally broken down into four phases although they are not exactly sequential: 1) specification of an exogenous parameter that controls the total quantity of land use change, 2) definition of the neighbourhood effect which details the relationship between land uses and governs the resulting local level land use patterns, 3) determination of the random perturbation parameter that adds a degree of stochasticity in land use distributions, and 4) calibration of suitability, accessibility, and zoning that reflect the cellular automata based dynamics in geographic heterogeneities. By adjusting 2), 3), and 4), the modeller creates the transition potential score (see Equations (6.1) and (6.2)), and then sets a cutline by specifying 1).

The calibration should start with the definition of exogenous constraints. The power of the Metronamica model, which links cellular automata dynamics to a broader socio-economic trend, lies here. However, it is important to note that there is a possible discontinuity of this parameter in calibration and simulation. To initiate the calibration, it is necessary to identify the total number of cells for each actively modelled land use type for the beginning and end calibration years. As a constrained cellular automata model, the Metronamica model allocates this quantity in the study space based on the transition potential scores. A misplacement of the global constraint would generate unrealistic results by allocating excessive or insufficient land use changes. A simple way is to count the number of cells from the land use maps. However, this is a physical observation which bounds the calibration results to the observed quantity of land use cells; it is not a socio-economic prediction or projection which can be used to generate future growth. The constraints for the future may be simply extended from the cell counts of past land use classes. However, if a socio-economic link is desired for the model, a new exogenous assumption, analysis, or projection of the land required is more desirable.

The calibration of the neighbourhood effect involves several decisions. The neighbourhood effect defines the influence of one land use on others within the predefined neighbourhood. In doing that, a modeller must decide the type of relationship between land uses as well as the magnitude of the distance dependent relationship. As depicted in Figure 6.2, it is a function of the distance and the strength of influence between land uses. The function can range from simple linear to complex concave or convex. Indeed the reason why automatic calibration methods are not yet effective for Metronamica is in the difficulty of identifying/estimating varying neighbourhood effects (Vliet and Delden, 2011). Not only is an automatic estimation difficult, but a manual specification is also challenging. To simplify the manual calibration process, the model can introduce a spline interpolation method. Then the specification of four control points which have fixed and parameterised X and Y values define the neighbourhood influence function. The first point should be on the (X=0, Y=neighbourhood parameter 1). The zero value of X means that it is the centre cell itself in the neighbourhood, and the parameterised Y value represents an inertial force to remain as a current cell state, i.e. a given land use type. The second point should be on the (X=1, Y= neighbourhood parameter 2). The distance 1 is fixed by the model, but Y value depends on user definition. The third point can be any distance between the second and fourth with any strength value (X= neighbourhood parameter 3, Y= neighbourhood parameter 4). The last, fourth, point should be located in the (X=max distance on the neighbourhood, Y= 0). This limits the spatial boundary of neighbourhood influence. From here and beyond, the neighbourhood effect becomes zero.

By specifying the values for the above four points, a modeller actually defines the influence function and its curve. Depending on the shape of function curve, cell transition dynamics would be different. The influence function is designed to encapsulate three forces in land use change dynamics: degree of inertia, degree of local agglomeration, and degree of attraction or repulsion between land uses. In a nutshell, the height and tail of the curve have important meaning to the resulting spatial patterns. For instance, a curve with a long tail produces larger clusters while that with no tail limits the growth of such a cluster. A low height function compared to one for other land use types tends to produce irregular cluster boundaries whereas the opposite case generates more rounded cluster edges.

Though simplified by an interpolation method, ranges of different curves can be defined by a user for a given study area. Finding the relevant neighbourhood influence function for a study area in a vacuum is like finding a needle in a haystack. Although the influence function should be unique to each application area in principle, Metronamica assumes certain common basic patterns can exist between land uses in a general sense. Thus the calibration of the neighbourhood effect in Metronamica often starts with ones used for previous studies, especially the one originally applied for Cincinnati, USA (White et al., 1997). Then these are finely adjusted for the given study area.

The next part of calibration is the determination of the random disturbance parameter. The random factor controls three aspects of emerging land use patterns: the density gradient of land uses, the seeding of new clusters, and the degree of irregularity of cluster boundaries (White and Engelen, 2003). In sum this determines the scatteredness of land use patterns as well as the geometry of individual land use clusters. A robust value of this parameter helps to preserve the stochastic nature of the urban system. Too low or high values result in unrealistic symmetry or disorder.

The final phase is adjusting suitability, zoning, and accessibility factors. Physical and institutional suitability can have an effect on calibration since together they form the function of transition potential. But these are more close to the description of initial (or interim) conditions, and thus they are less relevant to the model calibration. Accessibility is also a kind of condition, i.e. infrastructure. However, the influence weight is clearly a matter of calibration. It determines the degree of land use change influenced by varying the type of road network.

The most effective means of calibrating Metronamica is by visual map comparison, followed by iterative changes of parameter values and investigations on the goodness of fit. Globally aggregated statistical metrics are less relevant in determining the goodness of fit. The total amount of growth generated by the model will always be the same since it is globally constrained by an exogenous parameter, thus what is important here in the calibration process is comparing locally distributed patterns. Unfortunately an effective method to make a local level comparison is not yet available. Although the Map Comparison Kit can create cell comparison statistics such as the Kappa[28], Kappa Location[29], and Kappa Histogram[30], these are not good

[28] the product of Kappa Location and Kappa Histogram

[29] counts the locations simultaneously taken by each land use category

enough to compare locally distributed spatial patterns, especially the patterns generated by the varying neighbourhood effect. Consequently the best resemblance is judged by human intuition. Then the question is when to stop the calibration and by what criteria? Unfortunately there is no right answer for this as yet. It is the modeller's decision.

We calibrated Metronamica for the SMA in Korea. As an urban growth simulation, only urban land use types were considered as the actively changing land use types. The calibration period for the study area is an 8 year period. The model was calibrated using land use data from 2001 to 2009. It is questionable whether such a time span is long enough and whether that particular period is representative enough to capture the overall urban growth characteristics of the study area. However, this selection was determined by the best available data.

The calibration started from the actual land cover data for 2001, and then it was paused at 2009 to compare the result with actual land cover data at 2009. The total number of urban cells was counted for each year and used as the global constraint. The neighbourhood influence function for urban land use was initially defined by using the default function in Metronamica, and then it was gradually adapted to the study area. Urban land use is generally irreversible, and the study area also presents such a nature. Hence the influence function was set to have a high inertia value with a positive agglomeration effect. A random coefficient of 0.6 was used. The suitability and zoning layer were not adjusted for the calibration. The importance of the weight and distance decay parameter for the accessibility layer was decided in a way that the model reproduces a similar road influenced growth. As explained before, the model calibration had to rely on the visual map comparison with reference to the Kappa statistics. The map comparisons were repeated until a suitable parameter set is found. After repeated trial and error, the final parameter set was determined. Detailed values are presented in the Table 6.2.

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[30] compares the total number of cells in each land use each category

Table 6.2. Calibration Results

	Global Constraint		Neighbourhood Effect[a]		Random Coefficient	Accessibility Weight	
Value	Year 2001	590,275	Point 1	0, 10000	0.6	Highway	10, 0.25
	Year 2009	670,309	Point 2	1, 40		Main	10, 1
			Point 3	2, 12		Minor	10, 1
			Point 4	8, 0		Local	10, 0.5

[a] urban to urban interaction

However, the above method was for the calibration of local level dynamics. To simulate the model for the study area, a macro level land demand involving the global constraint, was necessary. A larger value for urban land demand would result in more urban conversion at the end of simulation, and vice versa. In order to make this logical, the macro level urban land demand for this simulation was derived from projected population growth for the study area. Many different factors contribute to the quantity of urban development, but it is generally reasonable to assume that population growth is one of the most fundamental causes of urban growth and sprawl (Cohen, 2004; Sierra Sierra Club, 2003). Based on the projected population growth published by the national statistical agency of Korea, it is assumed that the SMA will face continuous urban growth over the next 20 years. From the past trends of population and urban growth, the total demand for urban land in 2030 has been extrapolated accordingly.

6.4. Simulations

We designed three scenarios to simulate different growth dynamics generated by distinctive policy options: business as usual, greenbelt deregulation, and the introduction of high speed rail. There could be many different scenarios depending on the policy interests at hand, but these three scenarios are chosen to illustrate important and expected urban growth momentum for the study area.

While the first scenario focuses on the extension of the status quo, the second and third scenarios emphasise the effect of the new policy actions. Those scenarios are derived from ongoing planning policy agendas in the study area. Although these simulations are not engaged with the actual planning policy cases described in the scenarios, the research will illustrate how those policies would affect future urban growth patterns of the SMA and offer useful background knowledge to set future land development policy for the SMA.

In doing so, the model will highlight which growth scenario is more likely to cause urban sprawl or to lead to compact growth in terms of the spatial distribution of new urban growth. The main intention of simulation is not to see which policy option is likely to cause more urban conversion but to see how urban growth is distributed over the space depending on different policy options. It will not simply compare the total amounts of urban land generated by each scenario. It will instead contrast the distribution of urban land and resulting spatial form. It is possible to assume different amounts of urban land demand, but total demand for future urban land is exogenously defined from projected population growth and identically applied to all three scenarios in order to take advantage of the constrained cellular automata model. In this way, the model does not capture the difference in terms of the total amount of urbanised area and consequently all three scenarios would have the same amount of urban conversion at the end of the simulation year. By using the same constraint, the model will be able to capture the key differences amongst the different spatial determinants for each scenario.

The three scenarios, the 'business as usual', the 'greenbelt deregulation', and the 'new high speed railway', policy instruments are applied using the simulations with Metronamica. The model is run from 2001 to 2030 for each scenario. The simulation from 2001 to 2009 is used as the calibration period. However, the calibration of local level dynamics does not yield a value for the global constraint. For future simulation, a new exogenous assumption, analysis, or projection of the land demand is necessary. In order to make this simulation stand on a logical assumption, the macro level urban land demand for this simulation was derived from projected population growth for the study area. From the past trends of population and urban growth and the projected population growth published by the national statistical agency of Korea, the total demand for urban land in 2030 has been extrapolated accordingly. It is assumed that approximately 17.5% of the SMA would be the urban built-up area by 2030. Then the model is run until 2030 with different policy scenarios after the calibration. Details of the three scenarios including background information and the simulation results are discussed in the next section.

Scenario 1: Business as Usual

The purpose of the 'business as usual' scenario is to project future urban growth from the historical pattern. This scenario usually assumes the future as an extension of the past and present without further policy interventions and/or investment. It also assumes that the current population and economic growth will be maintained over time. However, in the case of this study area, it does not mean a scenario of accommodating maximum development. It is important to mention that greenbelts in the SMA are strongly maintained as usual in this scenario. So the result of the scenario would present the effect of the current greenbelt setting for future growth of the SMA. Other policies affecting current land use are less explicitly considered. A notable strength of the cellular automata model is that it can represent real world land use without using elaborated socio-economic data. Although this scenario does not explicitly address all current land use policies for the SMA, the model can efficiently extend the current trends through the key modelling elements such as the suitability condition and the interaction between land uses.

This scenario has two particular meanings for the future urban growth of the SMA. First, because no particular policy change is assumed in this scenario, it acts as a baseline scenario to compare other scenarios with certain policy options. Second, the future growth of the study area in this case depends on spontaneous urban growth forces under strong greenbelt regulation.

As presented in Figure 6.6, the simulation result shows that the SMA continues to grow and consume agricultural land as expected. According to the simulation results, the overall urban structure of the SMA would remain similar without any significant new urban concentrations. But without particular governmental actions other than the greenbelts, leapfrog development patterns mainly characterise the result of this scenario. Urban growth would occur in a dispersed way and continue to cause a loss of open space, and the number of urban patches and their degree of dispersion would also continue to increase.

As a result, the affected areas are mainly agricultural cities like Anseong, Hawseong, Osan, Paju, Pyeongtaek, and Pocheon. In fact, these areas are already experiencing urban sprawl problems because of their special status. The problem is likely to get worse if no policy actions are taken in the future. Although the model does not directly measure the negative impacts of sprawl, the negative effects of urban sprawl like traffic congestion and lack of infrastructure are already well known in the planning domain. Thus it can be inferred that this type of urban growth would also result in an increase in transportation and infrastructure costs.

This is hardly a desired societal future for the SMA. Then the question is how to prevent a worsening of this future and redirect new development in a preferable way. The following two scenarios explore the alternatives to this scenario.

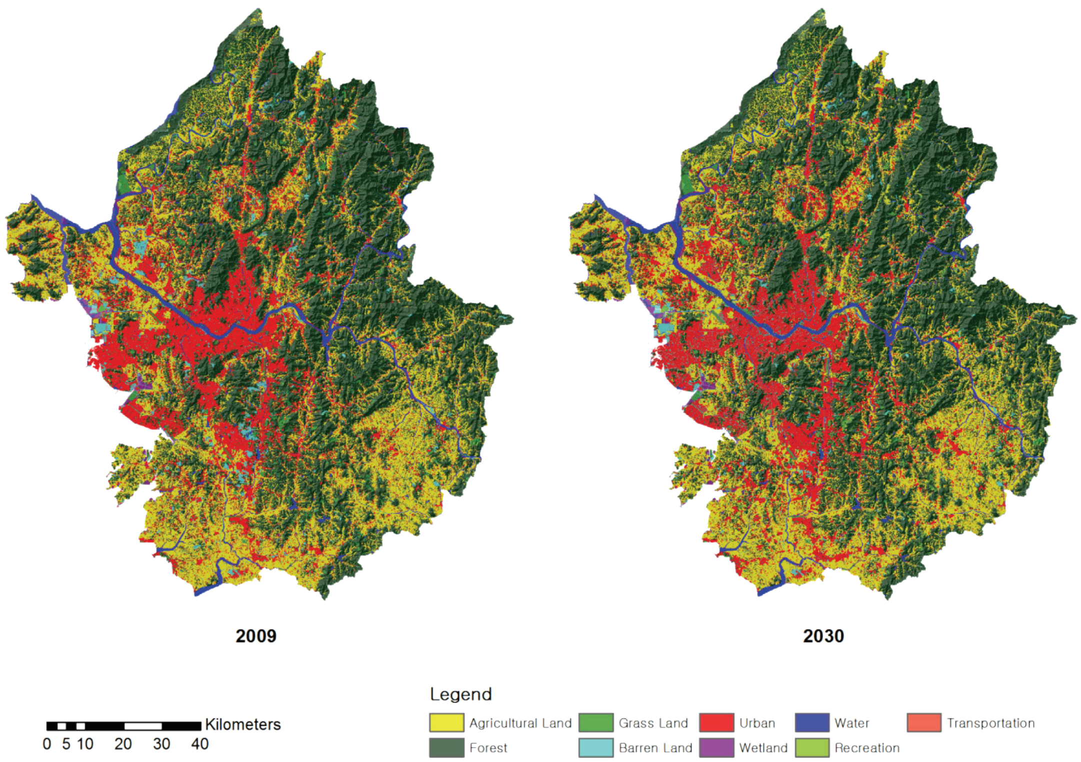


Figure 6.6. Urban Growth under the Business as Usual Scenario, 2009-2030

Scenario 2: Deregulation of the Greenbelt

The greenbelt in general has been an effective planning tool to stop excessive urban expansion and loss of open space. However, a positive consequence of protected open space is normally effective only within the designated area. A direct negative impact includes a distorted land supply, which affects the inside and outside of the greenbelt very largely. Land prices tend to rise in the inner ring of the greenbelt due to the shortage of available land, and the common reaction of the market is leapfrogging the greenbelt to get to the land outside the greenbelt. As a result, urban development continues on the outside of the greenbelt, causing urban sprawl at greater distances. The historic urban growth patterns of the SMA clearly confirm these trends. Dedicated economic studies have also pointed out the inefficiency of greenbelts such as higher land prices in Seoul. Choi (1994) argued that land prices in Seoul would have fallen by 7.5 percent if the greenbelt land had been released. In a similar sense, Lee (1999) argued that social benefits could rise from the marginal release of greenbelt land. Based on the analysis, the author concluded that periodic re-examination of the greenbelt designation is economically a better option than adherence to the original one.

This greenbelt deregulation scenario forecasts the future urban structure of the SMA in the case of the greenbelt removal. Although the efficacy of the greenbelt has been evaluated in an aggregate and aspatial sense, its spatial impact on urban growth has not been examined as fully. The main purpose of this scenario is to investigate whether or not the deregulated greenbelt areas could accommodate new development hence reducing urban sprawl outside the greenbelt. At the same time it also aims to forecast how such deregulation affects the loss of open space in the SMA.

To achieve this goal, simulations in this scenario are conducted under two sub conditions: planned partial deregulation and speculative complete removal of the greenbelt. Partial deregulation is currently being pursued by Korean governments as described in Table 4.5. Although various public development projects are planned in these areas, no specific government led development projects are modelled in this scenario. In terms of urban growth, those areas will be simply turned into urban land after the planned development. This scenario rather releases those areas without the assumption of public development to see whether or not it would be possible to reduce scattered urban development that otherwise would occur elsewhere in the SMA. This is seen in the results of the business as usual scenario. On the other hand, complete removal of the greenbelt has never been addressed by the Korean government or pursued by society at large. Although this is a purely hypothetical assumption of this study, it will more clearly expose the effect of greenbelt deregulation.

The simulation result carries important implications. Both partial and complete deregulation tends to result in sprawling urban development on agricultural land. However, they show different locational impacts on the SMA. Firstly, the partially deregulated areas are not really converted to urban land under the given circumstances. The size and scale of deregulation is not large enough to change overall growth patterns in the SMA. These deregulations may provide the necessary land for public development projects, but may not attract spontaneous urban growth because of isolation from existing urban centres and a lack of a transportation network. As a result, sprawling urban development occurs on agricultural land outside the greenbelt as in the results of the business as usual scenario. Indeed the result of partial deregulation is similar to that of the business as usual scenario. Agricultural cities at further locations in the SMA such as Anseong, Hawseong, and Icheon are significantly affected by sprawling development. Secondly, on the other hand, complete removal of the greenbelt creates a different spatial structure. Urban development would occur closer to Seoul city under this condition. Sprawling development occurs in Hanam, Ilsan, Goyang, Namyangju, and Siheung where undeveloped rich agricultural land now exists. As a result, agricultural cities at further locations such as Anseong, Hwaseong, and Icheon are less affected by urban sprawl. Figure 6.7 presents the result of the complete greenbelt removal scenario.

The result of this scenario reveals a paradox of greenbelt deregulation. Planned small scale release may not attract spontaneous urban sprawl within the released areas. However, this means it would not replace development pressure which could occur outside the greenbelt as well. It can be inferred that partial deregulation would create little room for new development, and urban sprawl tends to continue outside the greenbelt. On the other hand, complete removal of the greenbelt would mitigate sprawling urban development in remote locations, but this will endanger undeveloped areas previously protected by the greenbelt.

It is not the aim of this simulation to evaluate which area is more important to protect or not. However, it is important to understand that the protection or deregulation of the greenbelt should not be sought only on the shape of the greenbelt itself. The spatial impact spills over the greenbelt.

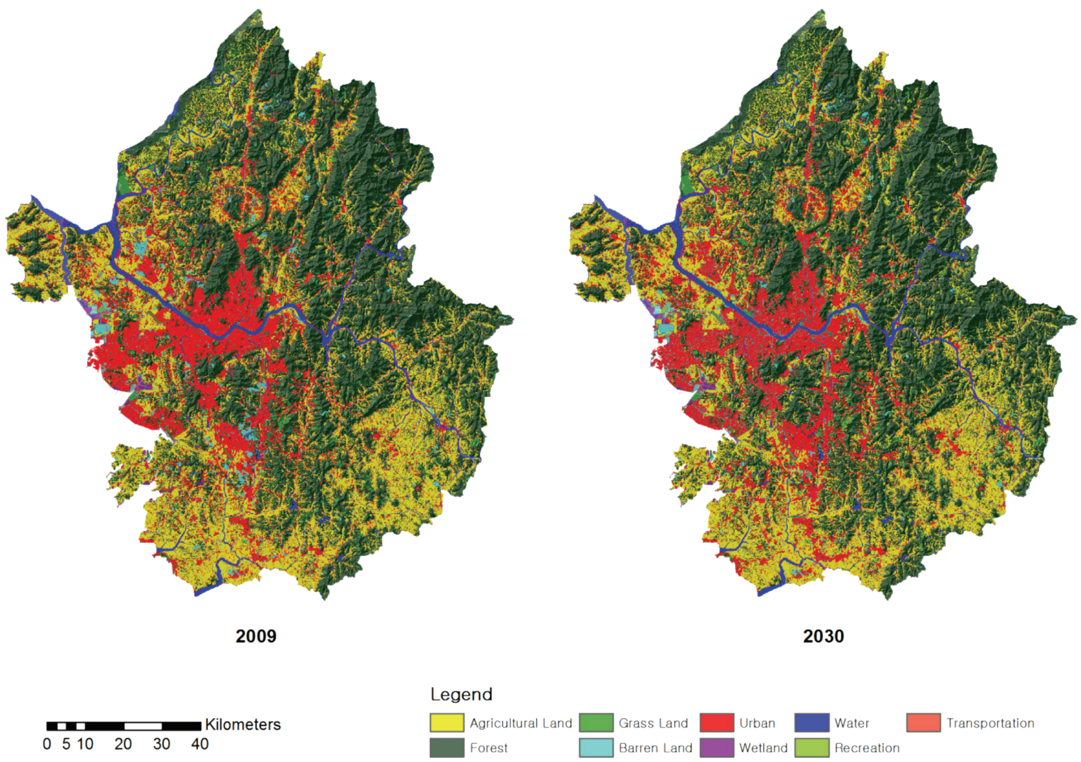


Figure 6.7. Urban Growth under the Complete Greenbelt Deregulation Scenario, 2009-2030

Scenario 3: Impact of High Speed Rail

This scenario examines how the proposed GTX would change the spatial structure of the SMA region under the condition of altered transportation accessibility. The proposed location of stations plays a key role for future urban transformation in this scenario. It is noteworthy to mention that the impact of the railway on an urban space differs from that of the road network. Unlike the road network, the accessibility is mainly increased around the stations in the case of a railway network.

The simulation results show a much more focused urban development pattern when compared to the previous two scenarios. Whereas the other two scenarios show no significant impact on preventing urban sprawl, the result of the GTX scenario presents reduced sprawling development patterns. This implies an important planning policy rhetoric. While preservation or deregulation of the greenbelt is not likely to attract spontaneous development into specific areas, the construction of the GTX is likely to pull urban development into the surrounding areas near railway stations.

According to the simulation results, the GTX would facilitate polycentric urban structure by imposing two important spatial impacts in the SMA region: centrifugal growth at the whole SMA scale but centripetal growth at the local scale around the proposed stations. Firstly, the GTX would redistribute development pressure from in and around Seoul city to further locations in the SMA by extending commuting distance with reduced travel time. Urban growth arises from the centrifugal power in this case. But it is different from urban sprawl in that the GTX stations tend to form local agglomerations due to better transportation accessibility. Hence, secondly, by shaping the new agglomeration centre at the local level, the GTX stations would pull urban development and thus prevent possible scattered development in other areas of the SMA.

The resulting patterns are new urban growth clusters around the stations in further locations in the SMA. Noticeably the impacts are not homogeneous across the entire line. Agglomeration effects prominently occur around Dongtan, Giheung, and, Ilsan, i.e. locations on the far ends of the proposed line A. Since the rail network increases transportation accessibility only around the location of stations, the areas in between the proposed stations are not greatly affected by the introduction of the new railway system. The stations in less urbanised areas are most likely to become new catalysts for future urban growth by providing efficient transport accessibility. On the other hand, some proposed stations located in already heavily urbanised cities, such as Uijeongbu and Geumjung, are not subject to further urban conversion although they are located on the edge of the line. The stations in the existing business districts of Seoul such as Cheongnyangni, Sindorim, and Yongsan would bring the effect of infill development, stimulating active conversion of vacant land into urban use. GTX stations in existing urban areas may bring another important spatial impact – urban regeneration or densification. However, this type of urban dynamics was not supported by the model. The result of this scenario is shown in Figure 6.8.

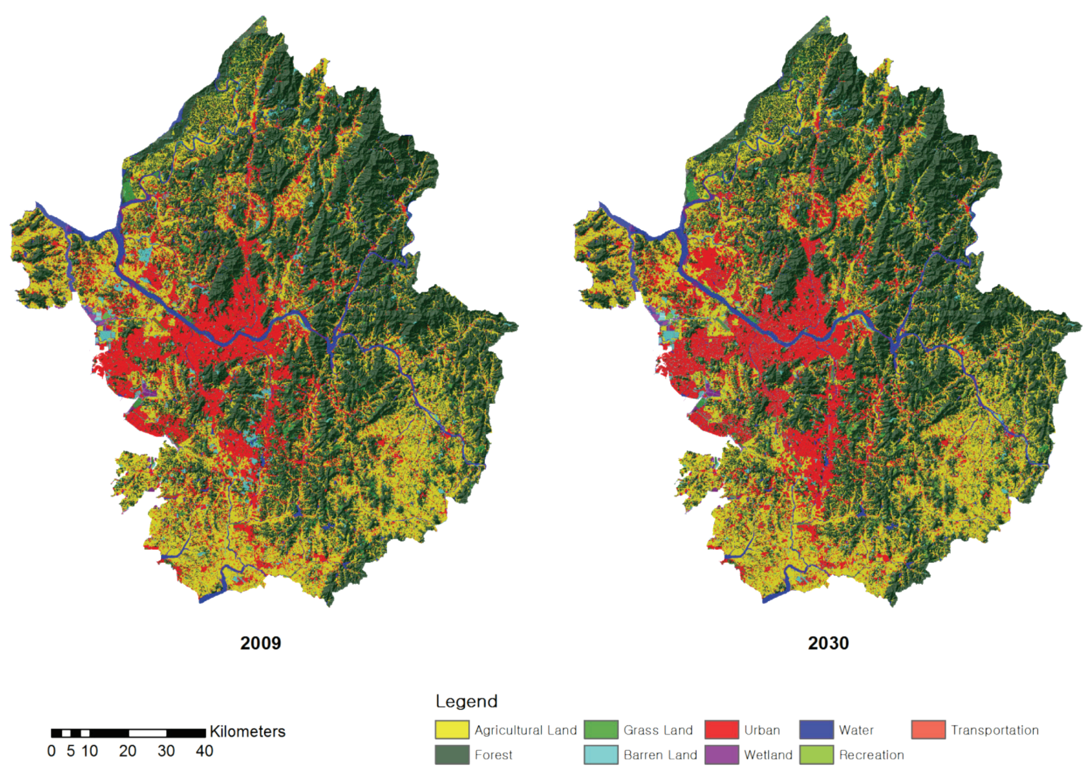


Figure 6.8. Urban Growth under the High Speed Rail Scenario, 2009-2030

The result of this scenario ultimately presents the possible outcome state of Transit Oriented Development (TOD). TOD is a local level urban development strategy empowered by public transit stations. It is considered as an effective means to foster compact city development as well as the economic development of local areas. The impacts and benefits of TOD are generally discussed at small local scales rather than regional ones. However, this simulation well illustrates how such transit based development as a whole would shape the regional spatial structure of the SMA.

Comparison of Results

This section compares the results of the three scenarios from two perspectives: the total area of urban land and the spatial distribution of urban development. Due to the nature of the Metronamica model and the constraint parameter used for the simulations, the former gives little difference across the scenarios while the latter presents more meaningful results. Details are as follows.

Table 6.3. Configuration of the Total Urban Built-up Area by Scenario, 2009-2030

Landscape Metrics / Scenario	Total Urban Cell Count	Urban Built-up Area(km^2)	Percent	Number of Urban Patch	Mean Urban Patch Size (Hectare)
Business as Usual				28,970	6.87
Greenbelt Deregulation	796,002	1,990.0	17.5	28,976	6.87
High Speed Rail				29,649	6.81

With regard to total urban growth, there is no difference between the scenarios because the amount of urban growth is exogenously defined with reference to projected population growth in this simulation. As a result, the total amount of urban land conversion at the end of simulation year is the same for all three scenarios. It is assumed that approximately 17.5% of the SMA would be the urban built-up area by 2030 (see Table 6.3). Although the number of urban patches and average patch size show a subtle difference between the scenarios, the urban area as a whole is almost identical across the scenarios.

On the other hand, Figure 6.9 and Table 6.4 highlight varied spatial distributions of different urban development scenarios and compare varying degrees of sprawl. A comparison of total new urban growth is made at a distance between 0-50 km from the centre of Seoul and this more clearly exposes the differences[31]. Having the same amount of total urban growth, Scenario 1 (Business as Usual) has the lowest amount of new growth within the 50km circle. Scenario 2 (Greenbelt Deregulation) shows more new development than the scenario 1 in the same range, and Scenario 3 (High Speed Railway) holds the highest amount of new growth within the 50km radius.

In summary, Scenario 1 maintains the current level of the greenbelt without further deregulation or transportation investment. It shows the most scattered development patterns. Scenario 2 assumes the removal of the current greenbelt. While such zoning deregulation mitigates urban sprawl in the outer areas of the SMA compared to the result of Scenario 1, it has a risk of causing sprawl in the inner areas of the SMA. Scenario 3 represents infrastructure development particularly on the high speed rail. This scenario shows the most focused development pattern. It displays meaningful urban clusters around the proposed location of GTX stations as well as infill development in Seoul city.

[31] The distance was measured from the location of Seoul City Hall, which is generally considered as the centre of Central Business District (CBD) in Seoul.

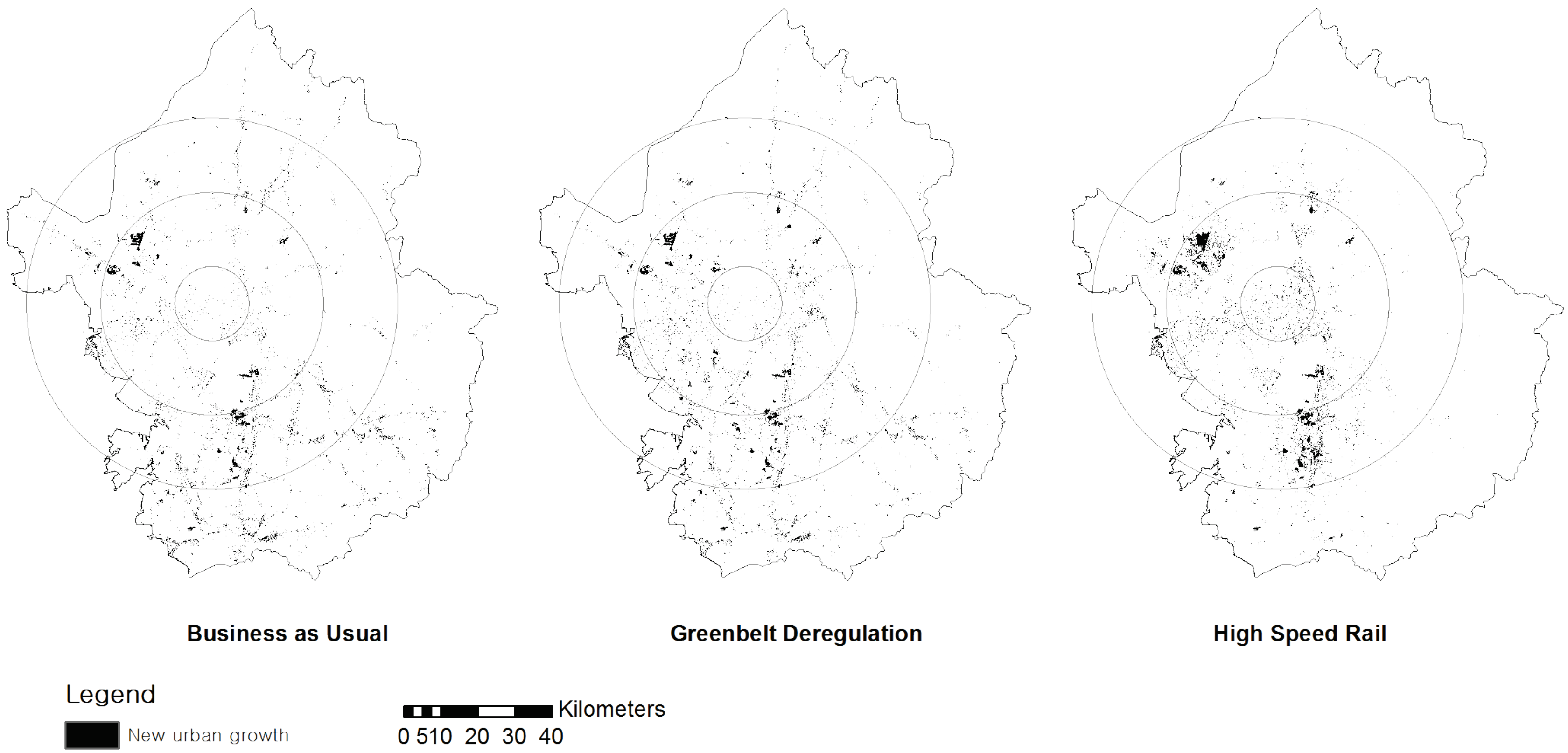


Figure 6.9. Comparison of New Urban Growth, 2009 - 2030

Note: The buffer rings are created at measured distances from Seoul City Hall. The rings have a radius of 10km, 30km, and 50km respectively.

Table 6.4. Comparison of the New Urban Growth by Scenario and Distance, 2009-2030

Landscape Metrics / **Scenario**	**Within 10km**		**Between 10-30km**		**Between 30-50km**		**Total (0-50km)**	
	Cell Count	Area (km^2)	Cell Count	Area (km^2)	Cell Count	Area (km^2)	Cell Count	Area (km^2)
Business as Usual	1,947	4.9	28,900	72.3	36,322	90.8	67,169	167.9
Greenbelt Deregulation	1,565	3.9	40,057	100.1	32,046	80.1	73,668	184.2
High Speed Rail	5,966	14.9	44,489	111.2	35,215	88.0	85,670	214.2

Note: Areas are calculated from the cell count (Cell size = 50 meter x 50 meter). The figures present the different outcome states between scenarios but should not be regarded as an accurate prediction of future growth amount.

6.5. Discussion

In this chapter, we calibrated a cellular automata based land use change model Metronamica to study the future urban growth of the case study area. Its unique approach to cellular automata modelling is reviewed and the model is applied to the case study area. To seek practical implications for the area, the study designed three scenarios: business as usual, greenbelt deregulation, and a new high speed railway system. Although the simulation results should not be taken as a rigorous prediction, this study has shown a way of understanding urban growth and of planning support with a dynamic urban growth simulation model. It has presented how cellular automata based urban models envisage the likely state of future growth and possible consequences of planning actions. As assumed and simulated, urban growth tends not to stop as long as the population and economy grow. On the other hand, urban growth is not likely to be completely uncontrolled or completely controlled in an institutionalised democratic society. Self-organisation is undoubtedly a main force of urban growth. The model was able to integrate such spontaneous development with the impact of planning policies. At this point, it can be logically inferred that the role of government policy is to understand such driving forces of urban development and to coordinate it with necessary intervention. Although the study considered a limited number of scenarios and factors, it could observe meaningful implications for the future growth of the SMA as follows. Spontaneous growth without any further investment or regulation is likely to result in continuing leapfrog development. Deregulation of the greenbelt could absorb spontaneous growth in further parts of the SMA but it would harm previously protected areas near Seoul city. Introduction of the GTX would promote polycentric urban structure and mitigate dispersed development, embodying the notion of Transit Oriented Development.

In terms of the discussion of cellular automata urban models, this study demonstrated that their constrained features have an advantage in incorporating non-physical features into the cellular automata dynamics. It also observed that the fixed amount of cell transition, land use change, has a certain strength in the comparison of alternative spatial patterns. The model could mark out more vulnerable or attractive areas for urban growth by synchronising total growth across the different scenarios, which highlights key differences between the scenarios.

There is a meaningful analogy between real world geography and cellular automata systems as Tobler (1979) suggested. While cellular automata urban models have shown their strengths in representing urban systems, most cellular automata urban models omit the influence of socio economic factors and only focus on the physical interaction between cells. Metronamica bridges the gap between the conventional cellular automata dynamics and land use as a reflection of socio economic activities. By joining the bottom up autonomous actions represented by cellular automata dynamics and top down controlling forces defined by constraints, the model effectively presents a complex behaviour of urban systems in a more realistic way. As we can infer from models of a similar kind, the modelling result could be identical whether it considers such social influences or not – i.e. mapped urban patterns. However, the model can tell us more about different determinants and processes of spatial patterns by assuming richer transition rules.

The rich transition rule set implies a complicated model calibration in turn. Yet the calibration of Metronamica is predominantly manual and qualitative. No single quantitative method can estimate the model parameters from observed data as yet. Consequently the calibration involves an iterative comparison of simulation results and actual data and a judgment by the modeller on the goodness of fit. The pitfall of subjectivity of course does exist in this process.

Paradoxically, however, such limitations suggest a range of new possibilities for CA based urban models. Firstly, it brings a 'sense of place' into the complex modelling framework as a key element. We believe that one who does not have a fair understanding of a given study area is not likely to calibrate the Metronamica model effectively. Secondly, a 'collaborative calibration' may reduce the impact of possible subjectivity issues in such a calibration process. In this case a modeller not only relies on his or her knowledge but also includes local experts and stakeholders to determine 'best fit parameters'. The consultation of local knowledge, which hardly exists in a quantitative form, would further enhance the understanding of the study area, and thus the advantages of such an approach would go beyond the determination of model parameters. Finally, less reliance on the data is another possible merit. Compared to a model using data oriented automatic calibration, this type of model is less dependent on the data at least in the temporal dimension. This would give the model a comparative advantage in supporting planning policies in 'data-poor' conditions.

Chapter 7: Towards an Agent Based Microeconomic Model

7.1. Background to the Simulation

Complex science based modelling frameworks such as cellular automata and multi agent systems have gained in popularity over the past decade in the study of urban systems, their spatial structure, and their temporal dynamics (Batty, 2005). This strength is firmly based on realistic representations of system behaviour through the explicit description of individual system entities and their interactions. However, although complex urban models provide a useful framework to understand the temporal dynamics of complex urban systems at a fine scale, their implicit representation of socio-economic factors reveals limitations in their use as decision support tools. The autonomy from available theory and heuristic approaches to simulating related model outcomes does produce rich system behaviours but this also results in limited explanatory power. In the past, these applications have been mainly centred on the study of self-organising urban morphologies with a focus on generative knowledge discovery (Batty, 2009; Crooks et al., 2008; Epstein, 2007; Manson and O'Sullivan, 2006; Matthews et al., 2007), and this has limited their applicability in real planning.

Recently a new approach to integrating urban economic theories into urban modelling frameworks has emerged through the study of land use change systems. The main benefit is not only stronger explanatory power from the perspective of agent based modelling but also a greater behavioural/spatial heterogeneity with respect to how the urban economy is modelled and represented. Combined together, these developments have the potential to offer a new type of dynamic and operational spatial policy support system to planning practice.

The bid rent theory and utility maximisation principle which forms the core of urban economics forms the common ground in this approach. While pure urban economic models mainly focus on finding and describing general spatial equilibrium conditions where an assumption is made that all economic agents are homogeneous, these new integrated approaches have generally paid attention to the effects of heterogeneous agents on the formation of urban structure. Brown and Robinson (2006) have presented various urban sprawl patterns resulting from heterogeneous preferences in the utility maximising location choice of households. Preference sets of households such as distance to local service centres, aesthetic quality, and social similarity have been selected from existing survey results on residential location choice. Caruso et al. (2007) modelled the emergence of diverse urban fringe formations depending on the effect of neighbourhood externalities and household preferences with respect to environmental or social amenities. Filatova et al.(2009) have implemented an agent based land market model with a focus on the interaction between buyers and sellers. Reproducing conventional concentric urban ring formations, the model shows that the magnitude of land rent distribution can vary according to the interaction between buyers and sellers as well as in terms of buyer preferences on proximity to the CBD or other local green amenities. Although the main focus of these researches varies, they usually pay attention to heterogeneity in agent behaviour and conduct simulations in an abstract theoretical space.

The main purpose of this research is to present an agent based urban growth model which integrates with microeconomic residential location choice theory. Previous work in this tradition suggests that varying preferences among a specific agent preference set undoubtedly has a significant influence on the formation of urban structure. This study notes this point but pays less attention to it for it focuses rather more on investigating the effect of spatial heterogeneity caused by local externalities and planning policies. It starts from the reproduction of conventional simple monocentric urban structure, and then presents the emergence and evolution of multiple urban agglomerations which arise from such spatial heterogeneity.

Economic theories are built upon certain simplifying assumptions in order to exclude less important conditions and minimise complexity of the real world. With regard to the behaviour of the individual, orthodox economic theories assume people are rational beings and they act to maximise their utility which is the economic term for self-interest. It is not the case in many other social science disciplines, but working with economic behaviour requires adopting these fundamental notions.

The basic spatial and behavioural configuration of the model to be developed here conforms to the fundamental assumptions of the Alonso-Mills-Muth framework. The space is an open city where in and out migration is possible without extra cost. The city generates a monocentric structure in the first instance, and homogeneous households commute to a single CBD. Total transportation cost for commuting is incremental to the distance from residential location to the CBD whilst households allocate their income on land rent for housing, transportation, and all other composite goods in order to maximise their utility. However, this study introduces additional features and releases certain constraints.

Firstly, the model deals with diverse spatial heterogeneities which result in polycentric and non-concentric urban growth patterns. Two main factors are investigated in this regard: local externalities that change location specific amenities and urban development that changes transportation costs. Although space is functionally still monocentric (based on a single CBD), the introduction of such spatial heterogeneities amends the utility function of households and eventually results in polycentric spatial structures.

Secondly, neither general market equilibrium conditions for land supply and demand nor partial spatial equilibrium conditions for the residential and agricultural use are considered. While demand side behaviour is explicitly defined by residential bid rent functions, supply side behaviour is only implicitly considered in this model. Land is assumed ready for residential use without any extra conversion costs. Absentee landlords accept the highest possible bid which is the same as the maximum rent that a household can pay. In short, there is no lag or disequilibrium in this market clearing process. Moreover, reserved agricultural land rent is not defined in this model. If the reserved agricultural rent were to be set, then transportation cost determines the size of residential expansion in a general bid rent approach. If the reservation bid rent for agricultural land is omitted, the city grows as long as there is in-migration and land available for development. As a result, agricultural land is not 'protected' by a market mechanism in this case, and there is no optimal growth limit to the city. Instead the growth limit imposed by agricultural rent constrains total urban growth as a kind of exogenous variable in this model. In this way, the model links with macro level demand or with external forces affecting urban growth. Indeed, this kind of approach to urban growth has been developed and is well described by the constrained cellular automata urban land use models developed by Engelen, White, and Uljee (1997) and White, et al.(1997).

In summary, micro level local behaviour is defined by short run utility maximising location choice in a bid rent function. Urban growth is attained as a sequence of such decision making in an agent based modelling framework. On the other hand, macro level global system behaviour is not subject to endogenous market equilibrium conditions. It is collective agent behaviour on the one hand and the location and magnitude of spatial heterogeneity on the other hand that shape global system behaviour and spatial configurations. Such spatial heterogeneity is assumed a priori, but here the government agency is also assumed to dictate spatial heterogeneity through zoning regulation or transportation development.

7.2. Underlying Theoretical Assumptions

The theory of urban residential location mainly pays attention to the location choice of households and explains urban growth with regard to the distance to central business district

(CBD), transportation cost to the CBD, and resulting residential bid-rent. Such a theory of urban residential location choice is fundamentally rooted in von Thünen's agricultural land use model but it is now more directly based on the work of the so-called new urban economists such as Alonso (1964), Mills (1967), and Muth (1969), who resurrected von Thünen and linked his work to more mainstream micro-economics.

Von Thünen's model firstly captured an important trade-off between land rent and transportation cost. The model is built on the following simplifying conditions. A centrally located single point as a city is surrounded by a featureless and homogeneous rural landscape. The market is located in the isolated city and all agricultural products are sold in the city. There are no roads, and farmers transport their own goods to the market. Farmers act rationally to maximise their profits. The resulting land use patterns are concentric rings around the city centre. Land use activities with higher profit tend to locate nearer the centre.

It was Alonso (1964) who reconstructed von Thünen's theory in an urban context. The work explains the agricultural, residential, and business land rent functions and bid price curves in order to establish a general equilibrium theory of urban land uses, but the main focus is on the residential land. Alonso emphasised the importance of residential land use in urban space and argued that although residential land use is a predominant land use form in an urban space it was neglected by previous theorists of land uses and values. Following Alonso, Mills (1967) and Muth (1969) further refined Alonso's residential location model through a simplification of the utility function and a redirection of the focus from land consumption to housing. These Alonso-Mills-Muth models together eventually formed a standard for urban residential location models.

The Alonso-Mills-Muth models together explain the behaviour of urban land use formation under the common assumption of a monocentric spatial configuration which results from the assumption that the origin of urban activity is at the core of a city, at its market around which everything else revolves. The urban space in these models is featureless except for the distance to a single employment centre, the central business district (CBD). Land is freely transacted between buyers and sellers who have perfect information about the market. A radial transportation system covers the whole city, and the transportational cost is proportion to the distance from the CBD. All households are identical, meaning that they attain the same level of utility. Households commute to the CBD and allocate their income on spatial goods (land or housing) and other non-spatial composite goods subject to income constraints. As the distance from the CBD increases, bid rent decreases due to increasing transportation cost. Built on many simplifying, hence rather unrealistic assumptions, the models have strength in deriving analytical solutions and theoretical austerity though a lack of reality to explain actual urban systems is inevitable. Yet, the models do yield important explanations for the formation of urban structure particularly in concentric rings around the core of the city based on the ability to pay rent for proximity to the CBD and the rest of the metropolis. In a nutshell, these location models encapsulate the core of human decision making as an economic agent and the interaction between such decision making and urban space.

Following Alonso-Mills-Muth, many extensions and applications have been developed to explain urban growth and sprawl under varying conditions. Some selected works are relevant to this study. Solow (1973) introduced the indirect utility function to explain residential land rent and suggested the possibility of polycentric urban structure with multiple local employment centres, also discussing an extension to embrace residential segregation derived from different income groups. Anas (1978) suggested a residential urban growth model in which the city grows as a sequence of short run residential equilibria. Fujita (1989) has also synthesised theories to describe equilibrium patterns of residential land use and urban structure. Starting from the basic monocentric model, he suggests extended models dealing with the effect of economic externalities such as traffic congestion and local public goods which further explain more diverse causes and results of urban form.

The monocentric model described by Fujita (1989) presents the Alonso-Mills-Muth tradition of residential location choice effectively. As is typical in the urban economics tradition, it is assumed that a household maximises its utility subject to a budgetary constraint. The utility maximisation of a household seeking a location in a city is mathematically described as:

$$\max_{r,z,s} U(z,s) \mid z + R(r)s = Y - T(r) \tag{7.1}$$

where *r* represents the distance to the CBD, z is the amount of composite consumer good, and *s* represents the consumption of land. The composite consumption good is treated as the numeraire, which implies its price is fixed at unity. The household makes a fixed income Y and allocates its income on the composite good, land rent at a given location *R(r)*, and the transportation cost at the location *T(r)*.

Such a utility maximisation problem can be addressed by another approach called the bid rent function. The residential bid rent is defined as the maximum rent per unit of land that the household is able to pay in order to reside at a certain location while attaining a fixed utility level. The bid rent function is described as:

$$\Psi(r,u) = \max_{z,s} \left[\frac{Y - T(r) - z}{s} \middle| U(z,s) = u \right] \tag{7.2}$$

The bid rent, *Ψ(r, u)*, is attained when the above land rent for a unit of land is maximised subject to the utility constraint. $Y - T\left(r\right) - z$ refers to the budget available for land rent which is obtained after transportation costs and consumption goods are allocated for. $\frac{Y - T\left(r\right) - z}{s}$ implies the land rent for a unit of land. Solution of the above maximisation problem also returns the optimal lot size in addition to the bid rent.

The determination of bid rent and lot size at a certain location is graphically illustrated in Figure 7.1. Two different consumption bundles which are both tangential to the indifference curve exemplify the changes in the bid rent and lot size with a change in the distance from the CBD. The maximum bid rent is achieved when the budget constraint is at a tangent to the indifference curve *u*. This means at the tangency point, the slope of the budget constraint equals the marginal rate of substitution (MRS) between the composite good and land. As a result, depending on the distance from CBD ($r1 < r2$), varying degrees of land consumption can occur. Since the transportation cost at *r2* is greater than at *r1*, the resulting land rent at *r1* is greater than at *r2*.

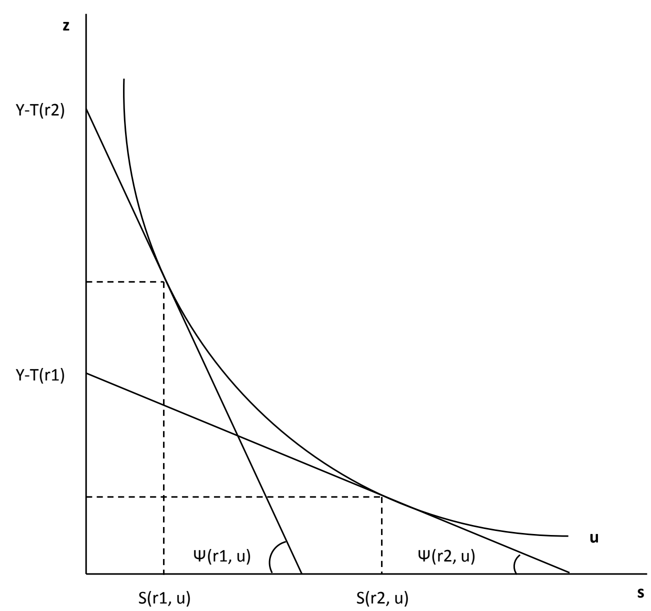


Figure 7.1. Bid Rent and Residential Location

A limitation of such a monocentric model is lack of reality. The standard monocentric model assumes a single employment centre and also ignores the influence of spatial externalities. That is, all business and commercial activities take place at a single focal point, the CBD, and households living in the homogeneous geography all commute to the CBD. The modification of such a monocentric model is generally achieved by considering neighbourhood characteristics or introducing multiple centres.

The neighbourhood characteristics include natural and non-natural factors such as demographic composition, public goods, and pollution that affect the preferences of households. Such consideration of preferences is more closely captured in the hedonic housing price model, but a way to incorporate the neighbourhood characteristics into the residential bid rent frameworks is to include location specific local amenities as arguments in the household utility function (Polinsky and Shavell, 1976). In the standard monocentric model, land rent declines with distance from the CBD. However, the introduction of such local amenity as green space or pollution can change the land rent gradient. If those spatial heterogeneities are taken into account, the residential bid rent is no longer a sole function of distance to the CBD but is also subject to various local characteristics. In this case, if the local amenities effect exceeds the transportation cost effect, the land rent will be increased even in a distant location (Straszhem, 1987). In this vein, Wu and Plantinga (2003) have developed a model to explain the influence of local scale environmental amenity in residential location choice where equilibrium land rent is not only a function of distance to the CBD but also that of environmental local amenities.

The introduction of polycentricity is a more radical solution. As is common in real urban systems, this type of urban economic model assumes more than one centre or sub centres. In cases such as this, the land rent increases in the immediate vicinity of all centres making multiple peaks of land rent. Fujita and Ogawa (1982) proposed a model of a polycentric city which results from the local agglomeration of business firms and the location choice of following households. Sivitanidou and Wheaton (1992) developed a bicentric urban model with a focus on different production costs in two centres and the resulting commercial land rent. Anas and Kim (1996) suggested general equilibrium models of polycentric cities. In the model, multiple equilibria emerge as production agglomerates into a number of centres. Debrezion et al.(2007) extended the model of Sivitanidou and Wheaton (1992) and further suggested the role of bimodal transportation in the formation of a polycentric city. Research of this type usually pays attention to the formation of polycentricity which is by definition the agglomeration of business firms as seen above.

Nevertheless, as in many theoretical economic models, these models are also static and focus on deriving long run stationary equilibrium conditions in featureless and continuous one dimensional spatial configurations while the effects of spatial heterogeneity are often ignored. The main focus of the proposed agent based urban growth model is on such residential agglomeration and dispersion. This study starts with simple monocentric models and then further augments the simple model by considering neighbourhood level spatial externalities and multiple transit modes. While the effect of spatial externality is generally included as an argument to introduce spatial heterogeneity in the utility and bid rent function, the introduction of a new transportation node introduces heterogeneity in transportation cost. This research presents how these two modify the conventional monocentric model in an agent based model framework.

7.3. Model Structure and Development

Basic Residential Location Choice

The basic behaviour of a household is a simple reproduction of conventional residential location choice. A household is assumed to have a standard Cobb-Douglas utility function for two types of goods and thus maximises its utility subject to the budget constraint:

$$Max\,U = g^{\alpha} h^{\beta},\ \alpha + \beta = 1 \tag{7.3}$$

$$y = g + hs + td \tag{7.4}$$

where g is the consumption of a non-spatial composite good (or numeraire), h is rent for housing, s is the size of housing land/plot, t represents the transportation cost which proportionally varies with distance to the CBD, and d denotes the distance to the CBD. α and β are the elasticity parameters.

The first rule in a utility maximisation problem is to yield optimal solutions for the numeraire good g and housing size s, which are given by substituting the MRS (marginal rate of substitution) into the budget constraint (2), that is

$$g^* = (\alpha / \alpha + \beta)(y - td) \tag{7.5}$$

$$s^* = (\beta / \alpha + \beta)(y - td) / h \tag{7.6}$$

Substituting the optimal consumption bundle of g and s into the utility function (1) yields an indirect equilibrium utility function:

$$U^* = \alpha^{\partial} \beta^{\beta} (y - td) / (\alpha + \beta)^{(\alpha+\beta)} h^{\beta} \tag{7.7}$$

Then the location specific bid rent for a household at location$_{xy}$ can be written as:

$$\psi_{xy} = [\alpha^{\partial} \beta^{\beta} (y - td) / (\alpha + \beta)^{(\alpha+\beta)} v]^{1/\beta} \tag{7.8}$$

In this standard monocentric model, a household faces a trade-off between transportation cost and land rent. Thus the bid rent always decreases as distance from the CBD increases. Under the competitive market assumption, the land rent will be the maximum bid. At the same time the residential location where the household is the highest bidder is also that of the maximum utility. The resulting spatial structure is based on concentric circles of differing land rent and hence land use around the CBD.

Extensions with Local Externalities

A notable extension of the standard monocentric model is achieved by considering location specific neighbourhood characteristics and local externalities. The types of local externalities affecting residential location choice include natural environmental factors such as green space, population density and composition, and public goods. Such externality effects can be either positive or negative, and this model deals with both cases starting with the former.

The effect of a local externality and varying neighbourhood characteristics are first incorporated as an argument into the residential location choice model. The residential utility function with the local externality *E* can thus be described as:

$$Max U = g^{\alpha} h^{\beta} E^{\gamma}, \ \alpha + \beta = 1, \ \gamma > 0 \tag{7.9}$$

Solving the utility maximisation problem with budget constraint (2) yields the location specific bid rent at location xy with local externality effect as follows:

$$\psi_{E_{xy}} = [\alpha^{\partial} \beta^{\beta} E^{\gamma} (y - td) / (\alpha + \beta)^{(\alpha+\beta)} v]^{1/\beta} \tag{7.10}$$

To define the local externality function, we adopt and modify the local amenity function used by Wu and Plantinga (2003). The positive local externality level at a location xy in this context is defined as:

$$E_{p_{xy}} = 1 + e^{-\theta d_{Ep(i,j)}} \tag{7.11}$$

where $d_{Ep(i,\,j)}$ is distance to the positive local externality at *(i, j)*, and θ is a distance decay parameter.

The above function gives a positive relationship between proximity to the local externality and the bid rent which increases as the distance to the local externality decreases.

This results in a rise of the land rent around the location of the positive externality, forming a polycentric urban structure. The polycentric residential agglomeration and the relevant spatial patterns will be presented in a two dimensional physical simulation environment in the next section.

While the effect of a local externality is usually examined in the above positive sense, this study further modifies the externality function and suggests a function of negative externality[32]:

$$E_{N_{xy}} = 1 + e^{-\varsigma / d_{E_n(i,j)}} \tag{7.12}$$

where $d_{Ep(i,\, j)}$ is distance to the negative local externality at *(i, j)*, and ς is a distance decay parameter.

Now the negative local externality returns a decreasing land rent as the distance to it decreases. The result is lower rent around the location of the negative externality and a concave spatial pattern towards it. The spatial pattern for this case will also be examined in the next main section.

Extension with Multiple Transport Modes

We now propose an extension for the case of multiple transportation modes. A standard monocentric model with extensions to deal with local externalities assumes only one type of implicit transportation, which is usually attributed to the private automobile. Previous sections showed that a possible polycentric urban structure could occur even in a monocentric configuration if there are effects of local externalities. In this extension, it is assumed that a

[32] Common examples include urban facilities like airport, landfills, and power plant that provoke 'NIMBYism'.

household faces a set of transportation modes for commuting and chooses the cheapest option to maximise its utility.

Consider the standard monocentric model once again. However, now suppose that a high speed rail station which implies a transit oriented development (TOD) is introduced by a government agent/agency. In such conditions, three types of commuting exist: by car only, by train only, and by a combination of the two. What to choose depends on the total cost of each alternative. A household minimises its transportation cost to maximise its utility, while commuting time and personal preference are not considered.

From the standard function under the monocentric condition (6), the bid rent with varying transportation costs can be rewritten as:

$$\psi_{T_{xy}} = [\alpha^{\partial}\beta^{\beta}(y - T_{\min}) / (\alpha+\beta)^{(\alpha+\beta)} v]^{1/\beta},\ T_{\min} \in \{t_a d_c, t_t d_c, t_{cn} d_{cn}\} \tag{7.13}$$

If this is combined with the local externality effect:

$$\psi_{T_{xy}} = [\alpha^{\partial}\beta^{\beta}E^{\gamma}(y - T_{\min}) / (\alpha+\beta)^{(\alpha+\beta)} v]^{1/\beta},\ T_{\min} \in \{t_a d_c, t_t d_c, t_{cn} d_{cn}\} \tag{7.14}$$

where t_a represents the unit transportation for automobile, t_t is the transportation cost for train, and t_{cn} denotes the total cost for combined use of car and train. In a similar vein, d_c is the distance to the CBD and d_{cn} represents combined distance to a transit station and the CBD. The commuting cost for train can be treated either as lump sum or unit cost per distance, but it is treated as the former in this thesis.

This function can also return physically polycentric urban forms even in its functionally monocentric configuration. If the commuting cost with train is cheaper than that with the automobile, then the bid rent price near a transit station is higher and the transit capitalisation effect occurs. However, the magnitude and size depend on the actual transportation cost and its elasticity. If nothing else is considered, cheaper train costs tend to result in a larger local agglomeration effect around the transit station.

7.4. Theoretical Simulations

The above functions explain short term decision making (location choice) behaviour of agents. We will run a series of theoretical simulations in order to examine and verify the behaviour of such microeconomic models in a two dimensional space. Now consider a Euclidean grid space $\Re^2$ with a horizontal dimension X = 50 and vertical dimension Y = 50 from the origin (0, 0). Suppose that a von Thünen style single point CBD is located at 1/2* X and 4/5*Y. Space is featureless except for the local externalities where the location of each externality will be given in each simulation.

In these theoretical simulations, only one agent enters the space to find housing location at each time step and the agent makes a location choice based on the functions defined in the previous section. The lot size is fixed to a single cell. Thus the cell is a spatial unit for urban conversion at each time step. The consecutive entrance of an agent and the cumulative settlement thus represent dynamic urban residential growth.

The location choice in a two dimensional space with an agent based modelling framework requires additional configurations regarding the initial location of the agent and its search/movement range (in terms of its neighbourhood configuration). The initial location of an agent may or may not have an influence on the simulation result, depending on the neighbourhood configuration. If an agent has scope for an unlimited search, i.e. the neighbourhood configuration is as big as the size of the entire space, the initial location does not affect the simulation result. In this case, an agent can search for ‘the best location’ in the entire space at one time step. However, if an agent has a limited neighbourhood configuration, it can find the best location only within its search scope. In fact, we use a concentric neighbourhood configuration with a radius of 8 cells – a total of 64 cells within the range of the location of the agent. The neighbourhood size is thus adjustable as a model parameter, but this is subject to the computing power available for the simulation and in very big cellular systems this might impose some limits. This point will be discussed in more detail later.

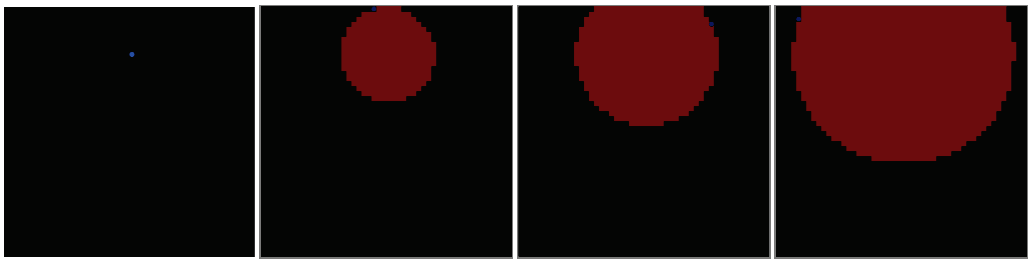
Parameter values used in the theoretical simulation are described in Table 7.1. As mentioned before, different preference values result in different spatial configurations. Defining such values is an empirical question, and possible variations with regard to the parameters are not explored in this work. It rather focuses on the effects of spatial heterogeneity with neutral and hypothetical parameter values.

Table 7.1. The Value of Parameters

Parameter	Value
α	0.5
β	0.5
γ	0.5
θ,ς	1
y	1000
t_a	2
t_t	10

A Simple Monocentric Model

The first simulation presents a standard monocentric growth without any local externality effect. In this well-known condition, urban form is always concentric with respect to the CBD. At the initial time step t = 0, only a single point CBD exists at the predefined location. As the time goes on, the locations in the immediate vicinity of the CBD are firstly taken by the household agent and converted into urban land. With no externality effect, the urban form is always concentric to the CBD. Thus urban structure keeps the same form with different volumes of development over time (t=500, t=1000, t=2000). A result of this simulation is presented in Figure 7.2.



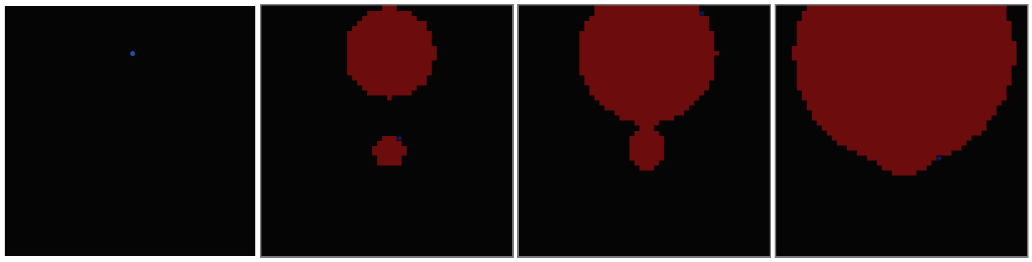
t = 0 t = 500 t = 1000 t = 2000

Figure 7.2. Monotonic Urban Growth

A Positive Local Externality Model

Now a positive local externality is introduced at the location 1/2*X and 2/5*Y. The introduction of such a local externality increases the amenity value radically around this location. Thus leapfrog development takes place due to the modified land rent distribution, and a polycentric urban form emerges (t=500). It is noteworthy that the urban expansion from the CBD is smaller than that of a simple monocentric growth at this same time step because the development occurs around the local externality. As the city continuously grows, agglomeration into a conurbation eventually occurs (t=1000). In the longer run (t=2000), the leapfrogged local agglomeration is absorbed into the main urban area, and the resulting spatial configuration becomes virtually identical to that of the simple monocentric one.

Figure 7.3 presents such urban growth patterns. It is worth noting that the assumption of a single constant externality can result in evolving spatial structures, and this exemplifies the value of this type of dynamic and spatial modelling approach.

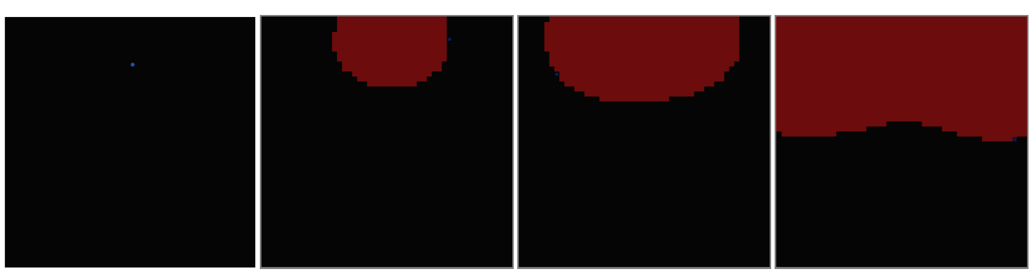


t = 0 t = 500 t = 1000 t = 2000

Figure 7.3. Leapfrog and Assimilation

A Negative Local Externality Model

Instead of the previous positive externality, a negative local externality is introduced at the same point 1/2*X and 2/5*Y. In this case the bid rent decreases as the distance to the externality decreases. As a result, the existence of this negative externality greatly changes the urban growth pattern from a very early stage. It takes a flat elliptical form because of the avoidance of the negative externality (t=500). The urban space further expands to the left and right edge rather than to the downward (t=1000). Although the distance to the CBD is greater on the edge, urban growth keeps moving to the left and right. Then it reduces from there while still avoiding the areas where the negative externality exists (t=2000). Figure 7.4 describes urban growth affected by the negative externality.

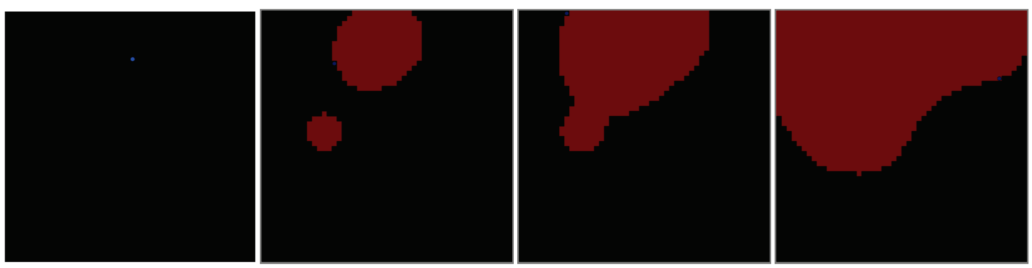


t = 0 t = 500 t = 1000 t = 2000

Figure 7.4. Pressed Growth

A Multiple Local Externalities Model

A combination of the positive externality at 1/4*X and 1/2*Y and the negative externality at 3/4*X and 1/2*Y reveals the following results. Urban growth around the CBD is skewed towards the source of the positive local externality from an early stage, and eventually leapfrogging development occurs (t=500). Then the evolution of the conurbation can be observed as the urban expansion from the CBD further approaches it (t=1000). Overall urban growth tends towards the location of the positive externality, and the area affected by the negative externality is largely left behind (t=2000). Figure 7.5 shows the urban growth pattern in the case of positive and negative externalities.



t = 0 t = 500 t = 1000 t = 2000

Figure 7.5. Skewness and Asymmetry

A Multiple Transportation Model

This simulation investigates the effect of a new transit station which implies the notion of transit oriented development (TOD). Consider a station that is introduced at the point of 1/2*X and 2/5*Y. As discussed before, this diversifies the number of transportation modes and changes the location specific transportation cost. At the beginning of the simulation, the city grows from its immediate surroundings in the CBD as typical in a monocentric configuration. However, as the city expands, polycentric urban structures emerge (t=500), with physical patterns similar to that of the positive externality case. But the driving force here is reduced transportation cost around the station and transit capitalisation benefits. Thus this simulation reveals a different urban growth path. Unlike the local externality effect, two urban agglomerations evolve together (t=1000). With no global equilibrium mechanism and threshold for agricultural rent, these are eventually merged together but retain their own form (t=2000). Thus it can be inferred that this type of urban development can lead to self-sustaining urban forms. The relative size of the two urban agglomerations depends on the difference between transportation cost for automobiles and public transit. This effect of transit development can also be combined with various types of positive and negative externalities, and it can explain why proximity to transportation nodes does not always return the higher land price in those cases. The effect of the introduction of a new transportation node is illustrated in Figure 7.6

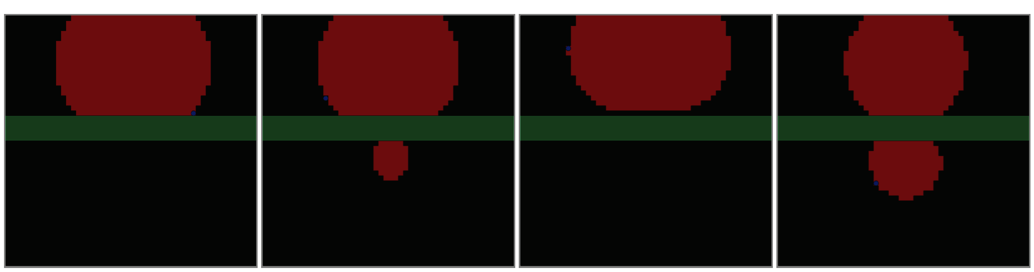
t = 0 t = 500 t = 1000 t = 2000

Figure 7.6. Leapfrog and Conurbation

A Zoning Regulation Model

The greenbelt, sometimes called the growth boundary, is one of the most powerful planning regulations on urban development. The effect of course varies by shape, thickness, and location of greenbelts (Brown, Page, Riolo, and Rand, 2004; Wu and Plantinga, 2003). However, this simulation argues that its effect also depends on what is outside the greenbelt. It captures the effect of greenbelts under different spatial arrangements at the same time stage (t=1000). In a monocentric setting, (a) the greenbelt blocks expansion of the city to a certain extent. The blocked urban growth expands to its left and right sides. In the case of a positive externality, (b) the greenbelt allows leapfrogging development from an early stage. It shows that the greenbelt may protect open space within the designated area, but it cannot stop the sprawl if a positive externality exists outside the belt. If a negative externality exists, (c) the city does not reach the boundary of the greenbelt at the same time steps. In this case, the greenbelt has no particular effect on stopping the growth but protecting its own open space. If the greenbelt is placed between two self-sustaining urban agglomerations, (d) it can create a buffer zone and prevent the emergence of a conurbation. It is also worth noting that the total demand and quantity of urban development is not reduced by the introduction of a greenbelt. As a result, development occurs elsewhere to compensate for non-development of the greenbelt area and this changes urban form.

These model outcomes represent rather well what has happened with the growth of Seoul, the capital city of South Korea. The greenbelt was introduced in the 1970's when Seoul itself was the only urban agglomeration in the capital region, and it successfully stopped the expansion of Seoul at a certain time point. However, growth eventually penetrated the belt and then leapfrogged the greenbelt. The rise and growth of new towns also touched the greenbelt from outside, and all these factors have meant that the effects of the greenbelt have changed in time and due to their surrounding conditions. The varying effects of the greenbelt resulting from different economic and spatial conditions are highlighted in Figure 7.7.



(a) (b) (c) (d)

Figure 7.7. Varying Effects of the Greenbelt

7.5. Empirical Simulations

The theoretical models introduced above are applied to a case study which enables us to investigate model implications for real world urban systems. The entire SMA area, which is the same as the study area for the SLEUTH and Metronamica models, was attempted first hand to run the model. However, the system was not able to allocate sufficient memory. Repast, plugged in a Java development platform Eclipse and running in a Java virtual machine, provides a convenient model development environment, but it is not an ideal tool for a high resolution and large scale model development which requires heavy computation work. It is worth noting that the dedicated model development, especially the one for the disaggregate and dynamic model, requires a fair amount of computing power as well as optimisation of computing resources. The issue was resolved by reducing the size of the study area.

The chosen study area is the southern fringe of Seoul, where the CBD is located at the north end of the study area. Figure 7.8 shows the extent of the area. It is based on a 25km by 25 km grid space with a cell size of 50m (giving a total of 250,000 cells). Most open space in this area, including agricultural land, has been protected by the greenbelt over the past decades. However, the government is now considering a partial release of greenbelt area in order to accommodate new development. In addition, there is an ongoing development plan for a new high speed rail system in the area. Although the main purpose of the new transit system is to facilitate commuting travel to the main business districts in Seoul, it is clear that the introduction of such new transportation systems would affect the future urban growth of the region. Two scenarios are thus tested. A baseline scenario releases greenbelt without further investment in public transportation. An alternative scenario considers the deregulation of the greenbelt as well as the introduction of a new transit station.

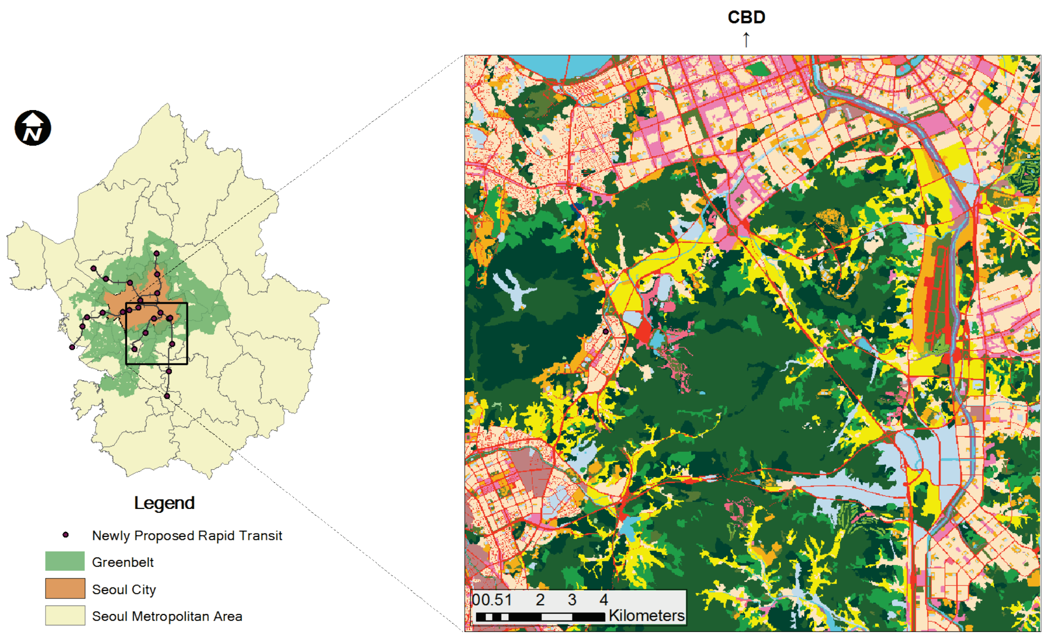
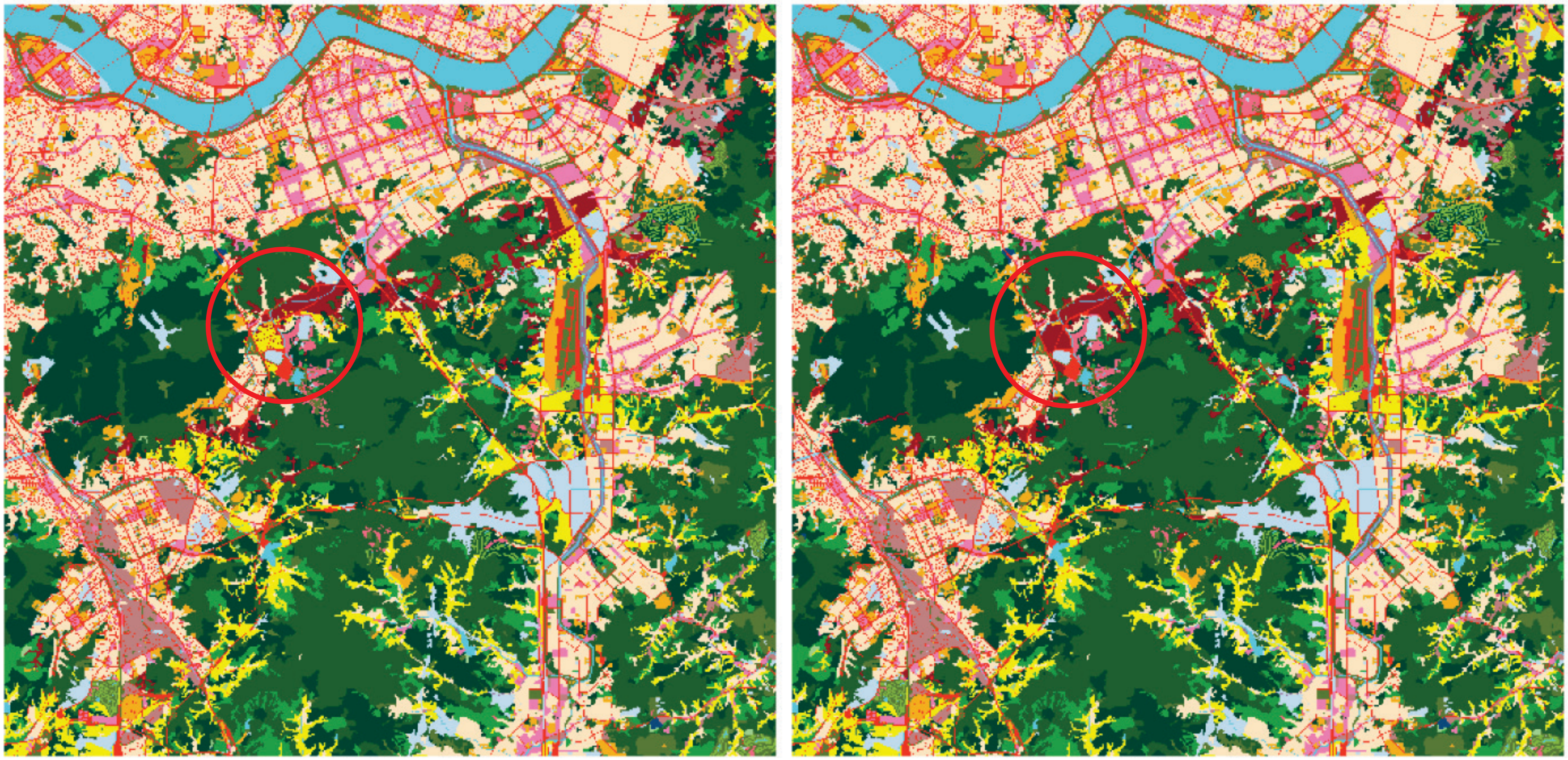


Figure 7.8. Study Area: The Southern Fringe of Seoul

It is assumed that urban growth occurs at the cost of agricultural land where agricultural land is the only developable land here. Thus the location decision of households converts agricultural land into urban land. Initially 1000 agents are placed in the space. Each agent searches for its utility maximising location and then moves to that spot. Once the agent finds its own residential location, it is removed from the simulation and a new agent enters into the space. The total amount of urban conversion is constrained by the exogenous global demand, and the simulation stops once the system reaches that threshold. Apart from utility maximising location choice principles, no other behavioural rules such as proximity to the road network are taken into account.

The simulation results show that the release of greenbelt undoubtedly allows development into areas of agricultural land. New developments however are likely to occur in closer locations to Seoul city in both cases. However, while both scenarios show small scale sprawling settlements due to the spatial heterogeneity and households' bounded rationality, the main difference in the results is the emergence of local agglomerations.



(a) Greenbelt Deregulation

(b) Greenbelt Deregulation with Transit Oriented Development

Figure 7.9. Comparison of Scenarios

The proposed location of transit stations plays a key role in the future urban transformation in these scenarios. The case with transit oriented development shows much more focused urban development compared to the other. Deregulation of greenbelt land is not likely to attract spontaneous development into specific areas, allowing sprawling urban development as we show in Figure 7.9.(a). On the other hand, the development of new transit stations is likely to pull urban development into the vicinities of the stations as in Figure 7.9. (b).

The simulations use hypothetical parameter values and are thus explorative. However these experiments reveal how location specific zoning regulations and urban development can affect the spatial decision making of individuals and alter the resulting urban formation. This has important implications for urban planning policy through the reciprocal interactions of self-motivated individual actors and public policy.

7.6. Discussion

In a typical agent based land use model, the location choices of agents are usually based on ad-hoc preferences which are hard to explain in a theoretical or empirical manner. However, in the integrated approach, an agent makes a location decision based on clearly defined self-interest – utility maximisation. However, in the proposed model, the agent not only faces economic constraints such as income and transportation cost but also considers geographic characteristics.

In this chapter, we have presented agent based residential urban growth models integrated with urban economic theory. The models proposed introduce explorations of various effects of spatial heterogeneity with a focus on location specific local externalities and transit oriented urban development. The simulations show how concise economic models can produce complex urban structures if they are combined in a dynamic agent based modelling framework.

The simulations also suggest that urban growth structures subject to constant growth can reveal different evolving forms over time.

The approach proposed here brings not only new research opportunities but also research challenges. The approach offers less reliance on heuristic algorithms, a more operational agent based model, an opportunity for spatial policy analysis with stronger explanatory power and the incorporation of richer system behaviour. However, for policy support, this study identifies two research challenges.

Firstly, empirical analysis of model parameters is necessary with regard to the explanations of household location decision making. It is clear the successful implementation of this type of agent based model greatly depends on empirical estimation of parameter values for the behaviour of agents. Integrating urban economic models with agent based models offers greater policy realism and model flexibility, but such simulation models can be used for practical policy support when this condition is fulfilled (Irwin, 2010). Indirect solutions to this can be developed using existing survey data. Brown and Robinson (2006) analyse data in the Detroit Area Study to define residential preferences. More direct solutions include conducting dedicated econometric estimations using random utility theory (McFadden, 1973). Specification of the deterministic parts of such models can be configured by indirect utility functions from bid-rent theory. The stochastic part can be modelled and estimated by logit or probit models. This also suggests that the integration of heterogeneous styles of models and analyses is inevitable as part of an enhanced agenda to better understand urban systems. Yet such efforts are not yet well coupled with the agent based models and this represents a key challenge.

Secondly, from the perspective of an agent based modelling framework, it can be concluded that this new style of disaggregate model still poses challenges for computing power although contemporary computers are much more powerful and efficient than those in the early days of urban modelling. Spatial resolution and neighbourhood configurations are directly subject to such computing issues. For instance, the limited search/movement space that we suggest here may have an analogy with bounded rationality and/or path dependency which in turn brings out unexpected system behaviour at global scale. However, in terms of operational modelling for policy support, this has important implications for the practical development and use of such models.

The above research challenges recall the critiques of Lee (1973). This modelling approach is still bounded by empirical data and computing resource issues. However, it is not a re-encounter of the same problems but an opening up of a new frontier on the way towards a better understanding of contemporary complex urban systems.

Chapter 8: Discussions and Implications of the Research Findings

8.1. Research Limitations and Future Work

Urban models eventually emerged to respond to practical urban problems and policy making. Although urban modelling has been eventually institutionalised as a distinctive academic domain, the link between urban model and planning policy is intrinsic (Batty, 1989). But the role of the urban model has been changing as the main fashion of urban planning is moving towards consensus building. Urban models are increasingly considered as frameworks for assembling relevant information, frameworks for formal and informal dialogues to support much more consensual and participative processes of decision making (Batty, 2009). Thus, the role of contemporary urban modelling not only includes the creation of rigorous scientific knowledge but also encompasses the exploration of various “what if?” scenarios.

While many different types of urban models have developed so far, cellular automata based urban models have gained in popularity over the past decades among urban modellers and planners to study the dynamics of urban systems and to evaluate the changes in urban spaces. More recently, similar but distinctive approaches to agent based modelling have opened new horizons for the study of urban systems. These models which are based on the notions of complex systems offer a new way of understanding urban systems. However, although cellular automata and agent based model are self-sustained modelling methodologies, they are often coupled with ranges of heterogeneous methods and technologies for the study of urban systems. Such cellular automata and agent based model approaches offer a promising modelling framework for urban simulation and policy support, but it is clear that the omission and amendment of some characteristics of complex systems are necessary in doing so.

In this context, this research firstly conducted experimental simulations with the generic cellular automata model SLEUTH and Metronamica for the Seoul Metropolitan Area. The SLEUTH model is a proven model to study urban growth systems and alternative policy scenarios, but the simulation results of SLEUTH in this thesis were limited by inadequate input data and consequently it could not draw useful policy implications for the study area. In terms of achieving a better simulation result, it is desirable to re-conduct the model calibration in future research with an improved data set. However, this experimental simulation has had an opportunity to investigate the unique quantitative calibration method of SLEUTH which is based on ranges of statistical correlation tests. Moreover, the simulation with SLEUTH also has provided a chance to consider the data requirement issue of dynamic urban models. On the other hand, the simulation with Metronamica was not limited by such data problems since this model requires less historic data. Thus, it could be possible to design meaningful policy scenarios such as the greenbelt removal and introduction of new high speed rail systems without a specific data issue, and this modelling practice has shown how cellular automata urban models can support planning policy by generating valuable knowledge about the likely states of the urban future. The implications of the calibration of SLEUTH and Metronamica will be further discussed in the light of the development and use of complex urban models in next section.

Then this research most importantly aimed at the development of agent based models as a way of modelling urban growth systems. A key difference between the cellular automata and agent based modelling systems is explicit representation of decision making entities and hence their decision making behaviour. To define such decision making behaviour, this research focused on the residential location choice behaviour originally established in the urban economics field in order to model urban growth systems. A classical mono-centric model is firstly defined based on the notion of Alonso-Mills-Muth tradition, and it is further extended with the notion of spatial externalities and multiple transit modes in order to simulate polycentric urban structures. Based on such microeconomic equation models, theoretical simulations are firstly conducted in the agent based modelling framework to examine model behaviour and then those models are applied to the case study area, the Seoul Metropolitan Area. The simulations were able to create various types of urban growth patterns along with different economic and spatial conditions. In addition, combined with external interventions such as the introduction of new a transit system, it was also possible to simulate the effect of planning policy options.

In order to use the model for practical planning support, one important task of further study is the development of the model calibration method – the determination of best fit parameters based on the analysis of empirical data. A key to the calibration of the proposed agent based model is an estimation of model parameters related to the bid rent functions. An independent econometric estimation of those parameters can return an empirical value for those preference parameters, but the sole reliance on those values would not assure the generation of an observed land use pattern. As a spatial model, the calibration over the locational characteristics of the study area would also be necessary. A practical solution can be learnt from the calibration method of SLEUTH or Metronamica – to find the best fit parameters by quantitatively and qualitatively comparing simulated and observed maps. This would also be an important agenda for the further development of the proposed agent based model.

However, the agent based model developed in this thesis is only a prototype model which examines the possibility of such an integrated modelling approach. The proposed model is kept simple to increase the feasibility of model development, and thus the proposed model is subject to further development in terms of model structure and parameters. Furthermore, the simulation with agent based models developed in this research is yet explorative because it relied on hypothetical parameter values with regard to the preference of agents. The model calibration has not been tried for these reasons. Thus, it would be necessary to add more reality to the model structure to use the model for a practical purpose, but the right level of reality varies by the very purpose of the model. Some practical elements such as heterogeneity among agents, heterogeneity of agents' preferences, and time matching are not attempted in this research, but it would be also useful to consider such elements to increase the reality of model behaviour and outcome.

Heterogeneity among Agents

One way to improve further the proposed agent based model is to add heterogeneity to the agent population. The research assumed a single type of homogeneous household, which is typical in conventional urban economics. That is, all households have the same income, utility level, and preference in housing location. Although such simplification delivers theoretical parsimony, consideration of multiple household groups would enable more diverse urban growth systems. In this case, each agent group will behave differently with different attributes and parameter values. For instance, if several different income groups are designed but with an assumption of homogeneous preferences, the model will be able to simulate the residential gradients formed by the income difference. If different preferences on the locations are taken into account, the model will produce varying urban growth patterns depending on the values of such preference parameters. The main merit of assuming heterogeneous agents is that the model can take account of varying decision making criteria by the differentiated agent groups. In this way, the model will be capable of showing how different agent groups together make up the urban growth structure.

Heterogeneity of Preferences

The bid rent approach mainly focuses on the trade-off between transportation cost and distance to CBD although it can be further augmented by the consideration of additional effects such as spatial externalities and multiple transportation nodes as demonstrated in this research. However, the bid rent model has a limitation in considering decision makers' various preferences on location choice. For this reason, random utility theory based discrete choice models are often used to explain a location choice among a set of choice alternatives. This suggests that the agent based model integrated with the bid rent approach also has an intrinsic limitation in modelling various preferences on location choices. The bid rent model offers theoretical simplicity and clarity, but if it is desired to maximise the reality in the agents' choice set, joining with another theoretical method such as the random utility based discrete choice model can be considered to better model the preferences of households. The value of such a method is already well proven, and its integration with random utility theory also provides a new avenue to address the behaviour of agents.

Time Matching

Matching simulation time with real time is another research task to further develop the proposed model. In a cellular automata or agent based model simulation, a discrete time step is equivalent to an iteration of certain modelled actions. At each time step, a certain change in the system occurs as a result, but how the time is associated with the change in the system varies by the modelling case. For instance, an iteration of four growth rules forms one growth cycle and it is regarded as a year in the case of the SLEUTH model. On the other hand, the calculation of transition potential scores and the allocation of land use change take place in each time step in the case of Metronamica. The Metronamica model allocates the total amount of land use changes defined by the exogenous parameter over the designated number of simulation years. Then the model considers one allocation of land use change as a year. The agent based model developed in this research relies on the use of abstract time without matching it with real time. However, for model calibration in future research, time matching is an essential element. Since the proposed agent based model constrains the total urban growth by a global parameter, a possible solution for time matching for this model is to globally constrain the amount of urban growth over the designated simulation years. This will be attempted in future research.

8.2. Implications for the Development and Use of Complex Science in Urban Modelling

This thesis carried out three independent but related simulation works. Each working block has offered its own findings and revealed limitations as explained before. In addition to this, it raises an interesting research question about which model or modelling approach better explains the urban growth future of study area. However, all models have their own strengths and shortcomings inherited from unique structures and methods. Moreover, those merits and demerits cannot be measured against absolute standard criteria but are relatively evaluated with regard to the nature of study area and problem on hand. No one approach or model is superior to others. In this sense, this thesis does not attempt to compare the performance models or the quality of simulation results. It is left as an open question.

Rather, this research attempts to draw some implications for the development and use of complex urban models for policy support in a more broad sense. The distinctive empirical experiences with the above models and modelling approaches within a larger complexity based urban modelling framework have provided the author with an opportunity to discuss the complexity of urban models in a more general sense. In this sense, the research identified several issues around the development and use of complexity in urban models and these are discussed in the next section. Of course, such implications and discussion are based on limited modelling practices in this thesis, and thus may not be applicable to the whole of urban modelling research and practice. However, we believe that the following comparisons in a broad framework can provide some useful implications for complexity in urban modelling and planning support.

Use of the Generic Model: Data Requirements and Functional Boundaries

Generic urban models are pre-packed and ready to use for a wide variety of study areas without further development or modification. The models can be used for a given study area following model calibration once the necessary input data are prepared and a modeller has necessary knowledge to run the model. Fulfilling specified data requirements is a first important condition for the successful implementation of generic models. In the use of dynamic cellular automata models, such data requirements are imposed not only on the spatial dimension but also on the temporal one. Cellular automata urban models tend not to demand comprehensive spatial and/or aspatial data compared to the different styles of LUTI urban model. As seen in the SLEUTH and Metronamica models, such models can be run with a range of spatial input layers but generate future urban patterns even without the use of complex socio-economic data. Both SLEUTH and Metronamica do not require historical data for future simulations and can be run from a single time point.

However, in terms of dynamic modelling, these models require historical spatial data to derive the best fit model parameters for future simulation and to ultimately bind the future simulation to empirical ground. SLEUTH requires more intensive historic data than Metronamica does. However, this does not necessarily simply give a comparative advantage to a certain model. This is inherited from their different approaches to model calibration which will be discussed in the next section. Nonetheless, this study faced a major challenge with attaining historical spatial data, especially for the transportation network. Although dedicated custom data building was a possible option, this study relied on the data available from public sector sources which is the usual situation in reasonably well developed countries and those like Korea that have rapidly developed in recent years. This is necessary so that we can conduct urban simulation with the best available data.

Every model has a unique structure, and hence it will have different data requirements. Whatever the requirements are, the model presents its own behaviour and outcomes based on such structure and requirements. Thus it is hard to evaluate a model simply with the data requirement. However, it is one thing that the urban modelling community should collectively think about. As Klosterman (2008) has pointed out, data available to planning practice tends to be inadequate but at the same time it is likely to be the best available data. Urban models should accommodate themselves to such conditions. In this way, urban models can be used not only by well-funded organisations but also by data-poor agencies and communities.

Furthermore, the use of generic models is bound to the functionalities of the model on hand. Although the model behaviour can be adapted to local characteristics through the use of location specific GIS data and locally adjusted parameters, the very ability to address a local specific planning problem is generalised to the modelled framework. As seen in this research, although SLEUTH and Metronamica were able to produce overall urban growth future of study area they also showed certain limitations in dealing with area specific planning issues such as deregulation of the greenbelt. The simulation with SLEUTH generated too much urban growth in the case of the complete greenbelt removal scenario. On the other hand, the simulation with Metronamica in the case of the partial greenbelt deregulation scenario could not capture possible future development in the deregulated area. As seen in these cases, generally the future scenarios only fitting to the behaviour of models can produce plausible results and meaningful implications.

On the other hand, the main merit of dedicated model development is of course its flexibility to address location specific urban problems. Development of dedicated models facilitates the handling of local specific problems in a customised way. The disadvantage is the time and cost necessary for the development and use of such one off models. This is not a new issue in urban modelling and again there is no one right approach for this. However, the development of small and extendible models based on a common modelling framework can provide a partial solution to this. The various types of theoretical and empirical simulations of agent based models presented in this research are built upon the Repast Simphony modelling framework. The use of such modelling infrastructure greatly reduces the time and cost for model development and this can be a practical solution between the use of a generic model and the development of a full scale model.

Calibration of the Complex Model: Data Centred vs. Knowledge Oriented Approaches

Another key to the use of urban models is model calibration. Although model calibration is a necessity for any model if a practical application is aimed for, generic models usually have pre-defined calibration methods. This research has witnessed two types of model calibration: using the systematic quantitative method of the SLEUTH model and the qualitative approach of the Metronamica model. The former uses empirical data to derive the model parameters while the latter relies more on the area specific knowledge for model calibration.

The data oriented calibration method of SLEUTH enables a semi automatic calibration process. Although the determination of the best fit parameter set is ultimately made by the modeller, the model performs all the necessary computations and sums up the statistical results to compare simulation outcomes and actual data. As a result, SLEUTH requires multiple years of historic data for urban and transportation layers. At the same time, while a quantitative calibration method provides an objective measure to evaluate the goodness of fit of simulation results, the method is still limited in measuring the simulation outcomes at aggregate and global level. This means that the best parameter set determined by considering such measurements has a firm statistical representativeness. However, the simulated future from those parameters is an extension from the aggregated and averaged model outcomes, not from local peculiarities. Unfortunately, quantitative individual cell level comparison is not well developed in this field.

On the other hand, the calibration of Metronamica relies more on the study area specific knowledge than on the data itself. Although repetitive visual comparisons are necessary, this enables the modeller to conduct in-depth investigation of local patterns. Such characteristics of model calibration are basically due to the complex nature of the model structure and the difficulty of estimating different strata of parameter values from the sole observed data of the land use map. An automatic extraction has been attempted (Straatman et al., 2004), but so far no single method has replaced a knowledge oriented calibration process specific to the Metronamica model. The pitfall of subjectivity of course does exist in this process. However, this does not necessarily mean such calibrations and hence the simulation results are unreliable. Compared to an automatic calibration based on statistical techniques, qualitative calibration has clear merit in bringing to bear knowledge on spatial forms and pattern specific to the modelled area. Indeed this is the *de facto* method that enables the close examination of the local level patterns since no quantitative metrics can yet fully replace such a method.

The quantitative estimation of model parameters from data is more general and common to scientific models. However, it should be noted that such effort is bounded by the availability of data as well as the quality of data. On the other hand, knowledge oriented methods are less dependent on the data at least in the temporal dimension as seen in these simulations. While this can be a weakness, this would give a model a comparative advantage in supporting planning policies in data-poor conditions.

Both approaches provide important implications for the calibration of proposed agent based models. One possibility of calibrating the proposed agent based model is adopting the automatic and quantitative approach of SLEUTH. In this case, simulations can be generated with all possible combinations of model parameter values. Then a best fit parameter set is decided by comparing the simulated outcome and the observed data. Such comparison can be based on a specific standard measure such as the LeeSalle metric, and the goodness of fit of model parameters can be evaluated using these criteria. Another possibility for calibration is the manual and qualitative approach of Metronamica. Although this approach is exposed to incompleteness and subjectivity, it offers an opportunity of more detailed comparison with human eyes and knowledge which is yet a *de facto* solution to investigate the goodness of fit at a cell level.

Model Development: Beyond Behavioural Realism

One of the main strengths of cellular automata is simplicity in model development. As demonstrated in Figure 3.3 to Figure 3.9, a number of simple rules can generate certain urban growth patterns at a global scale. Since such rules are typically constructed on an ad hoc basis, model building is possible without the use of tested theory. Established generic models such as SLEUTH and Metronamica add more diverse elements to reproduce real urban systems, but they also greatly rely on such ad hoc model development strategies.

Not confined to the established available theories, cellular automata urban models have partial answers to what theory based models could not answer – realistic reproduction of urban systems without reliance on unrealistic assumptions. Thus the main trends of cellular automata urban models have been centred on the pursuit of behavioural realism. The transition rules which form the core of such models mimic the behaviour of real urban systems based on an intuitive understanding of such systems. Then the models are calibrated over the observed land use data and used for practical applications, but the transition rules which generated the simulation results tend not to be examined further. Moreover, the use of the random algorithm is almost essential to maximise such realism as we have seen in the simulations in this research. As a result, although cellular automata urban models have been successfully applied to the study of complex urban systems, they lack explanatory power and have not yet effectively yielded theories about how urban systems evolve.

> “Endless ad hoc tinkering with the original cellular automata framework could yield model structures almost as complicated and inscrutable as the reality they purport to represent and that are as difficult to understand and interpret in a meaningful fashion. We would be back to the megasimulations of the 1960s and 1970s, and all the subsequent problems and criticisms that all but killed that particular line of research (Lee, 1973). The lesson learned is that, once complexity degenerates into complication, the game is lost”. (Couclelis, 1997)

As a way of overcoming such issues, this research has attempted to integrate urban economic theories into agent based modelling framework. As shown in the simulation results, the model could replicate realistic urban growth systems with more rigid theoretical explanations of the behaviour of agents. Although the proposed mode has many practical limitations to be further solved in future research, this approach provides a promising way of studying urban systems. Indeed recently emerging research efforts to infuse a more rigid explanation of urban systems into cellular automata or agent based model is slowly pointing to a new synthesis in urban modelling (Brown and Robinson, 2006; Caruso et al., 2007; Filatova et al., 2009). Such approaches usually introduce micro economic theories to define cell transition rules and/or agent behaviour. This type of approach is not yet fully developed, but this new trend implies a need for theory-oriented, disaggregate, and dynamic urban models. In this way, cellular automata and agent based urban models could provide much more realistic behavioural simulations of how urban structures emerge, evolve and regenerate themselves in such a way that they are useful and informative for enhancing policy and planning support.

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